Creating Opportunity: The Impact of Immigration on Native Entrepreneurship*

Gabriel Chaves Bosch†

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Abstract

This paper examines the impact of immigration on native entrepreneurship using rich social security data and a unique immigration episode in Spain. Using variation across local industries and employing a shift-share instrumental variable for identification, I find that immigration has a positive effect on native entrepreneurship. The effect is primarily driven by the entry of new native entrepreneurs transitioning from wage work, who tend to have above-median levels of education, previous wages and occupational skill, and to become incorporated entrepreneurs. I propose and calibrate a model of occupational choice and immigration to show the main mechanism driving the increase in native entrepreneurship is a decrease in labour costs. The immigration-induced labour supply shock lowers immigrant wages while having a limited impact on native wages. As a result, potential entrepreneurial profits rise, particularly among skilled natives, thus creating businesses that would not be profitable in the absence of low-wage immigrant workers.

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†Queen Mary University of London. Email: g.chavesbosch@qmul.ac.uk

Immigration is the main driver of population growth across high-income countries (IOM, 2024). Since most immigrants are of working age, their arrival represents a significant labour supply shock. Despite a large literature documenting the impact on native workers and firms,[1] less is known about how immigration affects natives' entrepreneurial choices. In theory, the effects are ambiguous. Entrepreneurship rates may increase if increased labour supply lowers labour costs, making business ownership more profitable, or if greater labour market competition displaces native workers into self-employment. Conversely, if immigrants complement native workers, wage employment may become more attractive, reducing entrepreneurship. These mechanisms have distinct implications. Profit-driven entrepreneurship expands labour demand, given the central role of small and young firms in job creation (Haltiwanger et al., 2013), while necessity-driven entrepreneurship may reflect lower opportunities and reduced earnings for natives. Despite the potential implications, we know little about how immigration affects natives' entrepreneurial responses.

This paper studies how immigration-driven labour supply shocks affect natives' entrepreneurial choices. I exploit one of the largest immigration episodes among OECD countries in the the post-war era: the sudden and unexpected inflow of immigrants to Spain in the 2000s.[2] Between 1999 and 2008, immigration expanded Spain's population by almost 5 million—more than 10% of its baseline population of 40 million. This episode was driven by the arrival of young, low-skilled immigrants from lower-income countries such as Ecuador, Morocco, and Romania.[3] These immigrants typically worked in manual low-wage jobs, often under temporary and informal arrangements (Amuedo-Dorantes and De La Rica, 2011; Bosch and Farré, 2014).

I identify entrepreneurs using longitudinal social security records that track individuals' employment status over time. This data allows me to classify individuals as either wage workers or self-employed, based on their contribution regime. Among the self-employed, I can further distinguish whether their business is incorporated or not. A key limitation is that I cannot observe whether they employ others, nor do I have access to firm-level information. Therefore, my definition of entrepreneur represents people who run the business they own, which is usually the case for small and middle-sized enterprises (SMEs), those firms with less than 250 employees. As of 2008, SMEs represented

[1] For a review on the labour market impact of immigration, see Dustmann et al. (2016) and Edo (2019). Recent literature increasingly examines the impact of immigration on firms (Dustmann and Glitz, 2015; Mitaritona et al., 2017; Imbert et al., 2022; Mahajan, 2024).

[2] Figure 1 compares the magnitude of the episode to countries often studied in the immigration literature.

[3] These are the top three origin countries, but many other people arrived from other Spanish-speaking Latin American countries and other Northern-African countries. Around 90% of immigrants arrived from lower-income countries.

99.8% of all firms in Spain, and contributed to two thirds of total employment (IPYME, 2009).

To estimate the impact of immigration on native entrepreneurship, I use variation on the exposure to the 1999-2008 immigration episode across local industries.[4] The use of local industry-level variation is central to the empirical strategy, as it enables precise identification of how native entrepreneurship responds to immigration within narrowly defined labour markets.[5] This granularity is essential to capture the labour supply impacts of immigration–such as changes in labour costs or interactions between immigrant and native workers–that are likely to drive occupational choice. My empirical strategy regresses changes in occupational structure and wages on immigrant changes from year 1999 to 2008 across local industries. The lack of immigration inflows before my study period and the use of the long-difference specification address dynamic sources of bias typically present in the immigration literature (Jaeger et al., 2019).

A key challenge is that immigrant inflows are endogenous to local labour market conditions: immigrants tend to move to areas with strong labour demand. To mitigate concerns about omitted variable bias driving the estimates, I use a modified version of the traditional immigrant networks shift-share instrumental variable (SSIV) pioneered by Card (2001). The instrument predicts immigrant inflows to province-industry cells by interacting pre-existing settlement patterns of immigrants across provinces with national inflows by country of origin, and distributing predicted arrivals across industries using historical employment shares by origin. This approach exploits the tendency of new immigrants to follow established networks in both location and industry choice, creating variation in local industry immigrant exposure that is plausibly unrelated to contemporaneous local shocks. The key assumption is that the initial distribution of immigrants across provinces and across industries, before the migration wave, is uncorrelated with subsequent changes in native entrepreneurship or employment in those province-industry cells, other than through the effect of increased immigration. To strengthen the case for this strategy, I show that the instrumental variable is robust to alternative definitions, does not suffer from serial correlation concerns (Jaeger et al., 2019), and both the instrument and its shares with higher Rotemberg weights are uncorrelated with pre-treatment outcomes (Goldsmith-Pinkham et al., 2020).

In the first part of the paper, I quantify and characterise the positive impact of immigration on native entrepreneurship. I find that an increase in exposure to immigration

[4]These are province-industry cells defined using the 50 Spanish provinces and a classification of industries into 5 groups, a total of 250 units.

[5]This is in similar in spirit to Card (2001), who stratifies local labour markets along occupation lines, instead of industries.

from the 25th to the 75th percentile across local industries results in a 3% increase in the number of native entrepreneurs relative to baseline average native employment in the local industry. Additionally, I find no effect on the number of native wage workers and a small but positive impact on native wages across local industries.[6]

After establishing the baseline result, I show that most of the increase in native entrepreneurship is primarily driven by incorporated entrepreneurs and high-educated individuals.[7] Incorporated entrepreneurship accounts for over 75% of the increase, while high-educated individuals account for around 83% of the rise, with significant overlaps between these two groups. Moreover, this analysis reveals that the positive wage effect amongst natives is driven by low-educated natives, with a negative albeit statistically insignificant impact on high-educated natives.

The positive effect of immigration on entrepreneurship is predominantly explained by an increase in the number of new native entrepreneurs. In principle, a positive impact of immigration on native entrepreneurship rates across local industries can be driven by either (i) an increase in entry to entrepreneurship, or (ii) a decrease in exit from entrepreneurship. I find that immigration boosts inflows into entrepreneurship while having no effect on outflows. This effect is almost entirely driven by transitions from wage work to entrepreneurship, specifically from individuals who were wage workers in 1999 but were entrepreneurs in 2008. Observing these individuals as wage workers in the baseline year allows me to investigate which types of workers transition to entrepreneurship after the immigration episode. I classify workers based on their baseline wages and occupational skill. The results show the inflow into entrepreneurship is driven by wage workers with above-median wages and those in medium to high skill occupations.

Finally, I assess how native entrepreneurship is affected by inflows and outflows across local industries. I find that approximately 75% of the effect is driven by new entrepreneurs who were previously wage workers in the same local industry. The rest of the effect is explained by new entrepreneurs who transitioned from other industries within the same province. This pattern suggests that, for most individuals, the decision to become an entrepreneur is driven by a comparison of changes in wages and potential profits within their current local industry, which is the basis of the model in the second part of the paper.

In the second part of the paper, I present a model of occupational choice in which

[6]Wage and employment estimates in this paper are instrumental to understand the drivers of occupational choice at the local industry level. However, they are not directly comparable to the total wage or employment effects at the regional level documented in other papers (Dustmann et al., 2017; Monras, 2020; Edo and Özgüzel, 2023).

[7]I divide individuals between high and low educated depending on whether their educational attainment is above or below the median, respectively.

natives choose between entrepreneurship and wage work to rationalise the results. Immigration represents a labour supply shock that alters both native wages and potential entrepreneurial profits. The model generates two competing channels: entrepreneurship may rise either because native wages fall or because potential profits increase.

To assess which mechanism aligns with the empirical results, I internally calibrate the model using reduced-form estimates and baseline data moments, and perform a counterfactual decomposition of the entrepreneurship increase. The results show that most of the increase is driven by higher potential profits due to lower immigrant wages, rather than falling native wages. This suggests that immigration encourages firm creation by raising the returns to hiring immigrant labour, rather than pushing natives into self-employment out of necessity.

The insights of this quantitative exercise, namely the relevance of lower labour costs driving the increase in entrepreneurship, are consistent with descriptive and empirical evidence. The rise in entrepreneurship is mostly explained by incorporated entrepreneurs, who are more likely to be employers.[8] Additionally, the fact that immigrants were mostly absorbed into low-paying jobs supports increased the availability of cheaper labour.[9]

Finally, I conduct a counterfactual policy experiment in which immigrant wages are subject to a binding minimum wage. This policy reduces native entrepreneurship by raising labour costs, particularly for marginal entrepreneurs. However, positive selection of more productive natives into entrepreneurship raises native wages. On net, average native income remains higher than in the pre-immigration baseline, but lower than in the original post-immigration scenario without binding minimum wages. On the other side, immigrants benefit from higher wages. These results highlight the distributional consequences of policies that restrict low-cost immigrant labour, and underscore the importance of accounting for native occupational mobility and heterogeneity in entrepreneurial productivity when evaluating the effects of immigration (Brinatti and Morales, 2023; Mahajan, 2024).

This paper contributes to several lines of research. More broadly, it builds on a substantial theoretical and empirical body of work that documents the impact of immigration on labour market outcomes of natives (Dustmann et al., 2016; Edo, 2019). Previous literature has focused on the effects of immigration on wages and employment (Gonzalez and Or-

[8] In 2008, two thirds of incorporated firms are employers, while only one third of unincorporated firms are employers, (INE, 2008).

[9] I show that the immigration episode was accompanied by a decline in immigrant wages relative to native wages, based on data from the formal sector. However, this likely understates the true disparity, as a substantial share of immigrants were employed in the informal sector, where wages are typically lower (Bosch and Farré, 2014; Elias et al., 2022).

tega, 2011; Foged and Peri, 2016; Dustmann et al., 2017; Edo, 2019), as well as on margins of adjustment such as internal migration (Piyapromdee, 2020; Monras, 2020) and occupational choice (Peri and Sparber, 2009; Amuedo-Dorantes and De La Rica, 2011; Foged and Peri, 2016). More recently, studies have emphasized the role of firm entry and labour demand in shaping natives' responses to immigration (Olney, 2013; Dustmann and Glitz, 2015; Beerli et al., 2021; Brinatti and Morales, 2023; Mahajan, 2024). However, this literature typically does not distinguish wage workers from self-employed individuals, or just focus on the former. My first contribution is to show that entrepreneurship plays a key role in absorbing immigration-induced labour supply shocks. Existing studies often focus on occupational shifts among wage workers (Peri and Sparber, 2009; Foged and Peri, 2016), but they do not account for how some natives adjust by creating firms and employing immigrants. This distinction is critical because, in contrast to wage workers, entrepreneurs reshape labour demand by hiring immigrants, influencing both equilibrium wages and employment composition. By explicitly measuring and modelling this response, I show that understanding entrepreneurial responses leads to a more nuanced understanding of immigration's impact.

My results also add to the literature on the impact of immigration on native entrepreneurship. Existing papers have focused on complementarities or substitution between native and immigrant entrepreneurs, as well as entrepreneurship as insurance to labour market displacement.[10] Focusing on the case of the United States, Duleep et al. (2021) highlight positive spillovers from immigrant entrepreneurs investing in new skills, while Fairlie and Meyer (2003) argue that immigration negatively affects native self-employment due to increased competition. Similarly, Unel (2024) finds that immigration reduces both incorporated and unincorporated entrepreneurship. In the context of the Portuguese *retornados* episode of the mid-1970s, Bohnet et al. (2022) identify a shift to low-quality solo self-employment, reflecting necessity-driven entrepreneurship among displaced natives. I contribute to this literature by providing new evidence, using rich administrative data, on transitions from wage work to entrepreneurship as a key margin of adjustment to immigration. Additionally, I propose lower labour costs driven by immigration as a novel mechanism impacting native entrepreneurship.

Finally, my work also relates to the literature on the impact of immigration on workers and firms in the presence of informality in developed countries.[11] Search models suggest

[10] In addition to these, Ajzenman et al. (2022) relate to this literature by showing that transit migration from refugees across Europe during 2010 to 2016 diminishes native entrepreneurship due to a decrease in risk-taking and confidence in institutions. However, it is difficult to establish to what extent the labour supply shock of transit migration is comparable to the labour supply shock analysed in these papers.

[11] Most of the literature on the impact of immigration in the presence of informality focuses on developing

that undocumented immigrants[12], in contrast to documented ones, have a larger positive impact on native labour market outcomes due to their willingness to work for lower wages, which reduces labour costs and raises labour demand (Chassamboulli and Peri, 2015; Albert, 2021). Empirical contributions are consistent with these predictions. East et al. (2023) show that increased deportations in the US lead to higher labour costs and reduced local consumption, thereby decreasing employment and earnings of natives. Additionally, Elias et al. (2022) study the 2005 regularisation of 600,000 immigrants in Spain, finding that low-skilled native employment decreased while wages of high-skilled natives increased. This result is potentially explained by the substitution of low-skilled for high-skilled workers due to the increase in labour costs following the regularisation. While my paper does not specifically address formality, I contribute to this literature by showing that labour demand adjustments occur not only through the intensive margin of existing firms but also through the extensive margin of firm creation. Additionally, I show that a immigrant-induced labour supply shock that lower labour costs–partially due to informal immigrant labour– and with complementarity between natives and immigrants, leads to an increase in native workers wages and entrepreneurs profits.

The paper is organised as follows. Section 1 describes the context, data, and descriptive statistics. Section 2 presents the empirical strategy. Section 3 provides the empirical results, and Section 4 proposes and calibrates a model of occupational choice and immigration to investigate the mechanism behind the results and policy counterfactuals. Section 5 concludes.

1 Context and Data

1.1 Context on the Immigration Episode and the Spanish Economy

The immigration episode. Spain experienced a massive immigration inflow from 1999 to 2008. During this period, the number of immigrants increased from less than a million to more than 5 million, over a baseline population of 40 million. The magnitude of this inflow makes it the largest immigration episode in the post-war period in any OECD country with the exception of Israel in the 1990s. In Figure 1, I provide a comparison of the immigration episode with respect to other countries usually studied in the migration literature. This figure shows two striking facts. The first is the magnitude of the episode, expanding

countries (Kleemans and Magruder, 2018; Altindag et al., 2020; Imbert and Ulyssea, 2023; Delgado-Prieto, 2025).

[12]Undocumented immigrants can only work informally, while documented immigrants can possibly work formally too.

the immigrant share of population from slightly above 2 per cent in 1995 to above 13 per cent in 2010. The second fact is that before the late 1990s, Spain was a country with very little immigration experience. Immigration flows into Spain during the 1980s and before were practically zero (Ortega and Peri, 2013). The reasons behind such a sharp increase in immigration during the 1999 to 2008 period are a combination of pull and push factors. The main pull factors were the economic growth of the Spanish economy, the ease of entering Spain, and the labour demand increase in tourism, hospitality, and construction industries, which offered mostly temporary manual jobs. Since Spain received immigrants from all over the world, the list of country-specific push factors is extensive. Some notable examples are the late 1990s crisis in Latin American countries, tightness in US immigration policy, proximity to Africa, and the European Union expansion. Consequently, the top three countries of origin are Ecuador, Morocco and Romania. To sum up, the suddenness and magnitude of this episode make it a unique opportunity to understand the impact of immigration on native outcomes.

Immigrants in the labour market. Immigrants during this episode were characterised by disproportionately working in manual low-wage jobs.[13] Immigrants had larger rates of participation in the informal sector when compared to natives (Bosch and Farré, 2014), and suffered from substantial occupational downgrading (Simon et al., 2014). In particular, by comparing official social security records and labour force survey statistics, Bosch and Farré (2014) find that, on average, 25% of immigrants worked informally throughout this period. This share of informal foreign workers is likely to be a lower bound due to the difficulty of surveying individuals not living in households (i.e. living in pensions or hotels) or temporary foreign workers without a residence in Spain. Putting all these considerations together, a native-immigrant job disparity arises, which also entailed a wage disparity. To illustrate this, Figure 2 compares distributions of native and immigrant wages before and after the episode in the formal sector, using administrative data. The distribution of wages changes substantially among immigrants by the end of the episode, due to (i) a change of composition from the immigrants who entered during the study period and (ii) immigrant competition lowering average immigrant earnings. In Table 1, I compare immigrants and natives aged 20 to 60 in the formal sector by the end of the immigration episode. Consistently with the previous graphical evidence, average wages of immigrants are substantially lower when compared to natives[14], with the difference likely

[13] Examples include construction workers, waiters, cleaners, caregivers or farm workers.

[14] In a Mincerian regression of wages on socio-demographic characteristics, I find that being immigrant vis-a-vis being a native has a substantial negative effect on wages, even after controlling for a large set of covariates such as age, tenure, gender, occupational skill (low, medium, high), industry and location.

being a lower bound due to the higher participation of immigrants in the informal sector. Taken together, this evidence is consistent with immigrants performing different jobs than natives and thus competing only with natives in low-skill occupations, if at all.

There is a large body of papers documenting the effects of immigrants on the Spanish labour market.[15] When it comes to the effect of immigration on the labour market, the literature agrees on a negligible effect of immigrants on employment and wages of natives from the 1999-2008 immigration episode. Using variation across provinces and by focusing on the 2001 to 2006 period, Gonzalez and Ortega (2011) find no sizeable effect of immigration on wages nor employment of natives. However, Amuedo-Dorantes and De La Rica (2011), by following closely the work by Peri and Sparber (2009) and focusing on the 2000 to 2008 period, show that this negligible employment effect among natives masks important relocation towards relatively less manual-intensive occupations. In particular, since immigrants in Spain specialised in relatively more manual tasks, which are usually more common in low-skilled occupations, this led natives to relocate to jobs with a lower content of manual tasks and in which they had a comparative advantage. Additionally, Amuedo-Dorantes and De La Rica (2011) show corporate managers, managers of small enterprises and other professionals are among the less manual occupations. These occupations are more likely to reflect self-employment.

Entrepreneurship among natives and macroeconomic context. The period of analysis saw a sharp increase in the number of native entrepreneurs. Table 2 shows that in my sample, composed of natives born between 1954 and 1979, the number of entrepreneurs increased by 86%, compared to a 19% increase in the number of wage workers. This employment growth was fueled by a period of buoyant economic growth, with an average yearly GDP growth of 3.5% during this period. Spain experienced rapid economic growth since the economic and political stabilisation that followed the 1992-1993 crisis, until the country was hit by the burst of the construction and credit bubbles, and the ensuing Great Recession, in 2008.

1.2 Data

I use four sources of data to study the impact of the 1999-2008 immigration episode on native entrepreneurship in Spain: administrative Social Security data on individuals working lives; administrative population registries; labour force survey data; and data from the 1991 population Census. In Appendix A.2 I provide additional information on the data.

[15] See De La Rica et al. (2014) for a review.

A. Muestra Contínua de Vidas Laborales (MCVL). First, I use administrative social security data to measure labour market outcomes for natives. This data includes the working lives for a representative 4% sample of individuals enrolled in the Social Security system. Records date back to 1966. The data provides detailed daily information on all working spells, including earnings, affiliation type (wage worker, self-employed), incorporation status if self-employed, occupational skill, industry, as well as socioeconomic variables such as date of birth, gender and education. Importantly, and in contrast with administrative data sets from other countries, a key feature of this data is that it includes information on self-employed (see Appendix A.1 for more information on the self-employed definition).

B. Padrón Contínuo. Second, to measure the immigration inflow, I use administrative data from the population registry for the period from 1999 to 2008. This micro data includes information on all people registered as living in Spain at the beginning of each year. This represents the universe of individuals living in Spain. Regardless of documentation status, immigrants have incentives to register to obtain access to public services such as healthcare and education. The universal coverage of the Padrón is key to quantifying immigrant stocks, which is instrumental to measure the immigration episode across space and time.

C. Labour Force Survey. I complement these sources of data with data from the Encuesta de Población Activa (EPA), the Spanish labour force survey, for the years 1999 to 2008. The survey nature of this data implies that informal workers are also captured. Since around 25% of immigrants, on average, were informal during this period, using the labour force survey allows me to quantify more accurately the shares of immigrants across different sectors by nationality. On top of this, the labour force survey is sampled using the Padrón as reference, thus improving representativeness of the estimates. I use the shares of immigrants across sectors to construct the immigration episode variable as well as the shift-share immigrant networks instrument. I also use the labour force survey data to construct baseline control variables across local industries.

D. 1991 Census. To calculate the shares of immigrants across provinces by country of origin in 1991, used in the construction of the instrument, I use data from the 1991 Census.

1.3 Sample

To construct the main sample of analysis for the outcome variables, I first build a panel of yearly observations at the individual level for the period from 1999 to 2008 from the MCVL. To create this panel, I use information on spells for native individuals, born be-

tween 1954 and 1979[16], and who were employed at least one year for a minimum of 100 days. I omit workers with missing place or date of birth, or province of residency. Individuals are classified as either wage workers, unincorporated self-employed, incorporated self-employed, or not employed, according to their main source of earnings for each year. Descriptive statistics on this micro data are provided in Table 2. I aggregate this information at the year by province and industry level to obtain local industry labour market outcomes for native workers.[17] I consider the 50 provinces of Spain[18] and an industry classification into 5 groups: agriculture, manufacturing, construction, retail and hospitality, and other services. Therefore, I end up with a sample that contains information of native labour market outcomes across 250 local industries. I refer to this sample as the analysis sample.

Descriptive statistics. In Figure 3 I plot the evolution of the main quantities of interest aggregated at the national level from 1999 to 2008, using the analysis sample. During this period, the share of immigrants over the working age population increases substantially, from 2.14% in 1999 to 14% in 2008. At the same time, the share of native entrepreneurs amongst employed individuals, increases by 6 percentage points, from 12% to 18%. Amongst these native entrepreneurs, the share of incorporated grows from 30.5 to 34.4%.

2 Empirical Strategy

2.1 Main variables of interest

This paper uses variation in immigration across local industries, defined as province-industry cells, to estimate the effect of immigration on native entrepreneurship and labour market outcomes. Therefore, the empirical strategy consists in regressing the change in a native labour market outcome at the industry level on exposure to immigration in that same cell between 1999 and 2008. The explanatory variable and outcomes of interest are

[16] These are the equivalent to the baby-boom generation in Spain, representing the majority of the workforce throughout the period. Since these individuals are highly attached to the labour market during these years, they are the most affected by the immigration episode of the 1999-2008 period.

[17] In the analysis I focus exclusively on the years 1999 and 2008, as I use a long-differences specification.

[18] I exclude the autonomous cities of Ceuta and Melilla, located in Northern Africa.

defined, respectively, as:

$$\Delta Imm_{ip} = \frac{Imm_{ip,2008} - Imm_{ip,1999}}{WAP_{p,1999}} \tag{1}$$

$$\Delta Y^N_{ip} = \frac{Y^N_{ip,2008} - Y^N_{ip,1999}}{Employed^N_{p,1999}} \tag{2}$$

where Equation 1 represents the explanatory variable, the change in the number of immigrants aged 20-60 in local industry ip, normalised by the baseline working-age population in province p in 1999. Then, Equation 2 represents the outcome variable, in this case the change in the native labour market outcome (e.g. number of entrepreneurs or wage workers) in local industry ip, normalised by the total number of employed natives in province p.

Next, I detail how I calculate the explanatory and dependent variables of interest.

Construction of the immigration episode variable. To quantify exposure to immigration within a local industry, I combine data from the Padrón Contínuo and the labour force survey. The Padrón is representative of the population living in Spain, so the idea is to calculate how many immigrants within a province are likely to work in a given industry, thus considering all working-age immigrants as potential workers.[19] First, I take the number of immigrants aged 20 to 60 in each province and year Imm_{pt}, from the Padrón Contínuo, and I multiply it by the share of immigrants in province p at year t that work in industry i, ω_{ipt}, obtained from the labour force survey. This gives me $Imm_{ipt} = Imm_{pt} \times \omega_{ipt}$, a measure of exposure to immigration in province p, industry i and year t. Therefore, the numerator of Equation 1 is given by:

$$Imm_{ip,2008} - Imm_{ip,1999} = Imm_{p,2008} \times \omega_{ip,2008} - Imm_{p,1999} \times \omega_{ip,1999}$$

Finally, for each province p, I use the Padrón Contínuo to calculate the number of immigrants and natives aged 20 to 60, which I define as the baseline working age population $WAP_{p,1999}$, which is the denominator of Equation 1.

I normalise by province-level working-age population rather than by local industry working-age population because imputing industry shares from the labour force survey can generate noisy denominators—particularly in small local industries with large immigration inflows—which results in implausibly volatile estimates of the immigration

[19] Previous paper looking at the labour market impact of immigration Spain calculate immigration flows using the Padrón as well, due to its reliability and representativeness when measuring immigrant stocks (Gonzalez and Ortega, 2011; Fernández-Huertas Moraga et al., 2019; Ozguzel, 2021; Castellanos, 2024).

episode.[20] Furthermore, note this is a measure of immigrant exposure in a local industry, not immigrant employment growth within that local industry. However, the two are highly correlated. Coefficient (1) in Table B6 serves as a first-stage, as it shows this variable is strongly associated with formal immigrant employment within a given local industry, as calculated by the MCVL. Finally, to relate this measure with previous literature, note that by summing the immigrant episodes across local industries within a province gives the change in the number of working age immigrants over working age population for that province, which is the usual immigrant episode variable used in papers using an spatial correlations approach (Dustmann et al., 2016), such as Ozguzel (2021) and Sanchis-Guarner (2023).

Construction of the dependent variables. To construct the dependent variables of interest, local industry labour market outcomes for natives, I use data from the analysis sample obtained from the MCVL, described in Section 1.3. The main variable of interest is the change between 1999 and 2008 in the number of native entrepreneurs in province p and industry i, normalised by province p baseline native employment, which is the sum of native wage workers and entrepreneurs in 1999. These are, respectively, the numerator and denominator of Equation 2.

To keep this measure consistent with the normalisation used for the explanatory variable, I normalise (changes in) native outcomes at the local industry level by province-level baseline native employment, calculated using the MCVL as well. [21] This normalisation ensures comparability across local industries. Finally, I measure wage changes as log differences of wages between 1999 and 2008.

Descriptive statistics. The variation in the aggregate data is consistent with the evolution of immigration and native entrepreneurs at the local industry level, as reported in Table 3. Across local industries, the number of both native entrepreneurs and wage workers grew. The growth in the number of native entrepreneurs accounts for roughly 30% of native employment growth. Native entrepreneurs, regardless of incorporation status, saw growth in their numbers as well. The change in log daily wages (in 1999 euros), obtained as residuals from a regression of wages on quadratic profiles of age and tenure, and occupational skill and year fixed effects, is negligible, at 0.4%, and not statistically different from zero. Regarding the immigration episode, the normalised average increase in immigration across local industries is of 4.4 percentage points between 1999 and 2008.

[20] These noisy estimates circumvent the relevance of the instrumental variable. To provide further robustness, in Section 3.4, I assess how robust are the results to using alternative denominators.

[21] Section 3.4 shows the results are robust using the number of employed natives in the local industry, instead of in the province, as denominator.

2.2 Estimation

My basic estimation equation regresses changes in the number of native entrepreneurs and wage workers on the change in immigration across local industries ip between 1999 and 2008,

$$\Delta Y_{ip}^{N} = \beta \Delta Imm_{ip} + \gamma' X_{ip,1999} + \gamma_p + \gamma_i + \epsilon_{ip}, \tag{3}$$

where the dependent variable is either differences in stocks of native entrepreneurs or wage workers between 1999 and 2008 in the local industry ip normalised by province p native employment, as defined in Equation 2, or changes in log wages. The explanatory variable are changes in the number of immigrants between 1999 and 2008 in the local industry ip normalised by province p working age population, as defined in Equation 1. I instrument this variable using the shift-share migrant networks instrument explained in the next subsection. $X_{ip,1999}$ is a vector of baseline controls at the local industry level which includes the native share of high education, share of males, share of entrepreneurs, the proportion of national employment in industry i accounted by the local industry, and the immigrant share. Then, γ_p and γ_i are province and industry fixed effects. Finally, ϵ_{ip} is the random error term.

The main parameter of interest is β, which captures the effect of a one-percentage-point increase in the immigration episode on native labour market outcomes. This identifies the partial effect of immigration across local industries—defined as province–industry cells—on native occupational choice and industry-specific wages. These estimates conceptually differ from those obtained using a pure spatial approach or skill-cell designs, as discussed in Dustmann et al. (2016). Whereas those approaches estimate aggregate or average effects across broader labour markets, the use of local industry variation allows for more precise identification of how native entrepreneurship responds to immigration-induced labour supply shocks within narrowly defined labour markets, where immigrant inflows alter input costs and sector-specific wages.

This design is particularly well suited to identify native entrepreneurial responses at the local industry level. However, the identified impact on native wage work and their wages is more prone to be affected by movements of wage workers across local industries. To provide evidence on the first claim, I first check whether there is entrepreneur reallocation across local industries. Columns (2) and (5) of Table 7 show that immigration has a negligible and statistically insignificant impact on the reallocation of entrepreneurs across local industries. Hence, the estimated effects are driven by new entrepreneurship creation, not entrepreneur reallocation across local industries. This is because the bulk of the entrepreneurship response is driven by wage workers turning entrepreneurs in the

same local industry (almost 75%), while the rest is driven by wage workers from other industries in the same province.[22] Finally, I assess the extent to which immigration affects wage employment through worker mobility. As shown in Table B7, while there is some reallocation of native wage workers across local industries, the net inflows and outflows are small and statistically insignificant.

Employing a long-differences specification across local industries has two main advantages. First, by using long-differences, I can take care of dynamic sources of bias, which would be present if I used a stacked regression with multiple shorter time periods and province and time fixed effects (Jaeger et al., 2019). Also, since my analysis sample follows the same cohort, the impact of compositional changes is minimised. Second, by splitting the sample by provinces, which roughly proxy local labour markets in Spain[23], and industries, I obtain more variation but also the opportunity to control for industry and province fixed effects. Province fixed effects are particularly important, which prevent β from capturing a demand-driven response due to general equilibrium effects of immigration (Mahajan, 2024), such as immigrant consumption, thus allowing me to identify the effect of the immigrant-induced labour supply shock.

2.3 Immigrant Networks Shift Share Instrumental Variable

Unobserved local labour demand shocks can affect both immigrant location choices and native labour market outcomes, potentially biasing OLS estimates of β from Equation 3. To address this concern, I estimate β using a two-stage least squares (2SLS) estimator, instrumenting the endogenous explanatory variable with the shift-share immigrant networks instrument pioneered by Altonji and Card (1991) and Card (2001). This instrument exploits the tendency of immigrants to settle where pre-existing networks are strong, which generates plausibly exogenous variation in immigrant inflows across local industries. Formally, the first-stage equation is:

$$\Delta Imm_{ip} = \delta \Delta \widehat{Imm}_{ip} + \rho' X_{ip,1999} + \pi_p + \pi_i + u_{ip}, \tag{4}$$

The instrument predicts immigrant inflows to province-industry cells by interacting national immigration growth by country of origin with pre-determined immigrant distri-

[22] These are the results from Table 10.

[23] Spanish provinces, designed by Javier de Burgos in 1833, roughly follow a Voronoi diagram, by which the edges of each province are equidistant from the province capital in each side. Since province capitals, and their metropolitan areas, are in most cases the most populated areas of each province, this implies spatial spillovers of shocks across provinces are limited. Thus, provinces serve as a reasonably good approximation to local labour markets.

butions across provinces and industries. It is defined as:

$$\widehat{\Delta Imm}_{ip} = \frac{\sum_c \left(\overbrace{(Imm_{c,2008} - Imm_{c,1999})}^{\text{Shift}} \times \frac{\overbrace{Imm_{c,p,1991}}^{\text{Province Share}}}{Imm_{c,1991}} \times \overbrace{\omega_{ic,1999}}^{\text{Industry Share}} \right)}{WAP_{p,1999}} \tag{5}$$

The shifts and the shares are defined as follows. The shift is the national-level change in the number of immigrants from origin c between 1999 and 2008, based on the Padrón. The province share is the fraction of immigrants from origin c who lived in province p in 1991, from the 1991 Census. Together, these predict the number of immigrants locating in a province, as in previous papers (Gonzalez and Ortega, 2011; Ozguzel, 2021; Sanchis-Guarner, 2023). Finally, to distribute immigrants across local industries within a province, I further multiply by the industry share, $\omega_{ic,1999}$, which is the share of immigrants from country c working in industry i in 1999, estimated using the Labour Force Survey.[24]

Identification relies on the exogeneity of baseline immigrant shares across provinces and industries, following the shift-share design in Goldsmith-Pinkham et al. (2020). Pre-existing immigrant networks and industry sorting patterns generate variation in predicted immigration across local industries that is plausibly orthogonal to other drivers of native labour market outcomes. For example, if Ecuadorians historically lived in Madrid and tended to work in services, a rise in Ecuadorian immigration to Spain would predict more Ecuadorians working in services in Madrid—not because of contemporaneous changes in the Madrid services sector, but due to pre-existing location and industry patterns.[25]

Therefore, the main identification assumption is that conditional on baseline controls $(X_{ip,1999})$ and fixed effects (γ_i, γ_p), the predicted immigrant shock to local industry ip must be orthogonal to omitted factors ϵ_{ip} impacting native outcomes in local industry ip:

$$\mathbb{E}\left(\widehat{\Delta Imm}_{ip} \cdot \epsilon_{ip} | X_{ip}, \gamma_i, \gamma_p\right) = 0$$

While this assumption is inherently untestable, in the next section I show that the instrumental variable passes key validity tests proposed in recent literature.

[24] Industry shares are calculated at the national level for each origin group c, rather than at the province level. This choice is driven by two concerns. First, province-level industry shares are more likely to be endogenous to local shocks. Second, sample sizes for some immigrant groups in specific province–industry cells are small, which would lead to noisy and unreliable estimates. National industry shares provide a more stable and representative measure of country-of-origin sorting patterns.

[25] The propensity of immigrants from a given country to work in certain industries can also be driven by country-of-origin advantages or preferences to work in that industry, as illustrated by Kerr and Mandorff (2023).

2.4 Assessment of the IV Design

In this section I analyse the validity of the IV design.

Conditional exogeneity. A main test used in the literature is to show that the instrument is uncorrelated with pre-period trends in outcomes. In Figure 4 I correlate the instrumental variable with outcomes prior to my study period. Pre-period outcomes before the immigration episode are not statistically associated with the instrument. All study period outcomes except the change in native entrepreneurship are also not affected, consistently with the evidence in Section 3. Moreover, the coefficients from the regressions of the instrument on the increase in native entrepreneurship before the period and during the study period are statistically different, with the test of the difference in coefficients having a p-value of 0.001. The lack of effect on outcomes in the pre-period is to be expected given how sharply immigration increased after 1999 and the virtual lack of immigration in preceding periods.

Autocorrelation of the instrument. A recent criticism of the shift-share IV based on immigrant networks is that immigrant inflows tend to be correlated over time (Jaeger et al., 2019). This phenomena can blur the identification of the impact of current immigration inflows with adjustments to previous immigration inflows. Serial autocorrelation becomes even more concerning when using yearly variation. Indeed, this is one of the main reasons why I use a long-difference setting. While the 1999-2008 immigration episode in Spain featured a sharp unexpected increase in immigration, I test whether controlling for pre-existing immigration growth affects the results. In Table B3 I show that controlling for pre-existing immigration trends from 1996 to 1999[26] and using the multiple instrumentation procedure suggested by Jaeger et al. (2019) does not alter the results.

Alternative instruments. I show that the results remain robust to using alternative instruments. First, I show that the results remain virtually unchanged when using a push-factors instrument as in Sanchis-Guarner (2023), where a "0-th" stage is included, where the predicted quantities of immigrants from Equation 5 are predicted using a plethora of indicators from World Bank data across all countries of origin. The results remain virtually unchanged, consistent with the fact that for many countries, push-factors were important in driving migration. Second, in Panel C I show the results of a leave-one-out (LOO) specification. The LOO instrument subtracts the number of foreign born population from country c in province p at time t, $Imm_{c,p,t}$ from $Imm_{c,t}$ in Equation 5, thus using only the number of immigrants in other provinces to calculate the shifts. Using a LOO also does

[26]The Padrón Contínuo data is only available from 1996.

not alter the results.

Rotemberg weights. Recent literature has highlighted tests to assess exogeneity in shift-share instruments when identification comes from the shares (Goldsmith-Pinkham et al., 2020). A main concern is that initial shares of country-of-origin groups may be endogenous. To provide further evidence on the exogeneity of the shares, I test whether these are correlated with pre-period outcomes. I first calculate the Rotemberg weights of each country-of-origin share. The top 5 countries/areas of origin in terms of Rotemberg weights are Ecuador (22%), Rest of America (20%), Colombia (12%), Bolivia (10.5%) and Romania (8.5%).[27] Next, I test for correlation between initial shares of immigrant groups and pre-period outcomes. The estimates in Table B5 show mostly non-statistically significant correlations, although with some correlations in pre-period changes in employment and wage work with shares of Bolivians and Romanians. Overall, and in particular for pre-period growth in entrepreneurship, most correlations are insignificant.

Relevance. Finally, I show the instrument is relevant by exploring the identifying variation in the first stage described in Equation 4. In Figure 5 I provide scatter plots of the immigration episode on the instrument, naively in Panel (a) and then netting out covariates and fixed effects in Panel (b). In both cases, there is a clear positive relationship. Even after netting out covariates and fixed effects there is enough residual variation in the instrument to identify the reasonably exogenous variation due to immigrant networks and pre-existing preferences of immigrants of different countries to work in certain industries. In Table 4 I show how the first stage coefficient remains significant after the inclusion of controls and fixed effects. In Column (4), the first-stage F-statistic is 23.11, well above the $F = 10$ cutoff.[28] Therefore, the instrument satisfies relevance and displays useful identifying variation.

3 Empirical Results

This section presents the empirical results, using the identification strategy outlined above.

[27] Rest of America includes mostly Latin American countries like Honduras, Guatemala, Venezuela, Uruguay, etc.

[28] Throughout the empirical results, I provide the Kleibergeen-Paap rk Wald F statistic, which in the case of one instrument and one endogenous regressor is equivalent to the first-stage F-statistic. The associated 10% maximal IV size critical value is 16.38, and hence the F-statistic still remains above, which provides further confirmation on the relevance of the instrument.

3.1 Native Entrepreneurship, Employment, and Wage Effects

Table 5 provides the results of estimating β from Equation 3 for a set of native employment and wage outcomes. For completeness, in panels A and B, I estimate β using OLS, while in panels C and D, I use the 2SLS estimator. To assess the robustness of estimates to controls, in panels A and C, I estimate the model omitting baseline controls. Neither instrumenting nor adding controls makes a substantial difference in estimates, suggesting that there is no strong selection of immigrants into particular local industries. Hereinafter, I use the specification from Panel D.

The main result is that immigration has a positive impact on native entrepreneurship. Column (3) of Table 5 reports the impact of immigration on the change in the number of native entrepreneurs. I find a positive effect of the immigration episode on the change in the number of native entrepreneurs. In particular, a one percentage point increase in the immigration episode–which corresponds to 0.33 of a standard deviation– increases the growth in the number of native entrepreneurs in a local industry, as normalised by the baseline number of native employed workers in the province, by 0.23 percentage points (a 7.8% increase from the mean increase in the dependent variable).

Is the native entrepreneurship effect large? Using a back-of-envelope calculation, I estimate that the an increase in exposure of a local industry to immigration from the the 25th to the 75th percentile results in an additional increase in the number of native entrepreneurs of 3% with respect to baseline native employment in a local industry in 1999.[29] This is equivalent to around a third of the native entrepreneur increase from 1999 to 2008.

Finally, I examine the impact of immigration on native employment and wages at the local industry level. I find no significant effect on native employment. Column (1) reports the results for total native employment—combining both wage workers and entrepreneurs—while Column (2) focuses exclusively on wage workers. In both cases, the coefficients are small and statistically insignificant. In contrast, Column (6) presents the results for native wages, where I find a small but positive effect, statistically significant at the 10% level. However, these wage estimates should be interpreted with caution. In settings with worker reallocation across local industries, observed wage effects may partially reflect labour supply responses rather than purely equilibrium price changes.[30]

To assess the relevance of mobility responses, Table B7 documents patterns of native

[29] This is calculated as $\frac{\hat{\beta} \times (X_{P75} - X_{P25}) \times Denom(Y)}{Employed_{1999}}$ where $\hat{\beta} = 0.232$ is the estimated regression coefficient, $X_{P75} = 0.0627$ and $X_{P25} = 0.018$ are the 75 and 25 percentiles of the immigration episode, $Denom(Y) = 19476$ is the weighted average of the denominator of Y, at the province level, and $Employed_{1999} = 6453$ is the weighted average employment across local industries in 1999.

[30] Similar internal reallocation across regions has been documented in other contexts using province- or city-level variation, such as in the U.S. (Monras, 2020; Piyapromdee, 2020).

worker relocation. While there is some movement—particularly natives relocating to industries within the same province that experience larger immigration inflows—net inflows and outflows are statistically indistinguishable from zero. This suggests that the observed wage effect is unlikely to be driven, on average, by changes in the relative supply of native workers. Instead, it points towards interactions in production between native and immigrant labour within the local industry as a more plausible driver.

3.2 Heterogeneity

The positive effect of immigration on native entrepreneurship raises the question of which type of natives are driving this increase. Immigrants may impact entrepreneurship by impacting the opportunity cost of entrepreneurship, i.e. native wages, or potential profits, as they may impact input prices, i.e. wages of both natives and immigrants themselves. Generally, the impact of immigration on immigrant wages is negative due to the own-price elasticity being negative.[31] However, the impact of immigration on native wages depends crucially on the patterns of complementarity or substitutability between immigrant and native workers. This motivates an analysis by skill, as patterns of substitutability or complementarity with respect to immigrants may differ by skill.

Table 6 provides a decomposition of the main results using education as a measure of skill. Across education levels, there are no effects of immigration on the number of employment or wage worker levels among natives. However, among low educated native wage workers (those with secondary education or less), there is a positive wage effect. The wage effect turns negative for high-educated workers, although insignificant. When it comes to entrepreneurship, there is a positive effect on entrepreneurship from all educational levels, although only statistically significant among high-educated individuals. While at baseline people with high education represent around half of the sample (see Table 2), they account for more than 83% of the positive effect of immigration on native entrepreneurship.

Previous literature has found that higher education attainment is correlated with high-quality entrepreneurship (Levine and Rubinstein, 2016, 2020). This is consistent with the results being driven by incorporated entrepreneurship–typically used as a proxy for high-quality entrepreneurship–, which accounts for 75% of the increase in native entrepreneurship, as already indicated in Columns (3) to (5) of Table 5. When zooming into education, most of this increase in incorporated entrepreneurship is explained by high educated individuals, as Column (5) from Table 6 shows. While the effect is predominantly driven

[31] This is a consequence of assuming perfect substitutability, which is reasonable in this setting. Figure 2 shows average immigrant wages decrease during this period.

by high educated natives in incorporated entrepreneurship, there is also part of the effect explained by high-educated unincorporated native entrepreneurs, as well as some low-educated incorporated native entrepreneurs.

3.3 Entrepreneurship Flows

Comparing cross-sectional quantities misses important dynamic adjustments explaining the effect of immigration on native entrepreneurship. The impact of immigration on the stock of entrepreneurs may be driven by either increased inflows into entrepreneurship or reduced outflows from entrepreneurship, both from other labour market states (non-employment or wage work), or from other local industries. In this subsection, I use the longitudinal dimension of the data to investigate how immigration impacts flows between entrepreneurship and other labour market states, as well as flows across industries and provinces.

Flows across labour market states. I define flows as the number of people transitioning between different labour market states, which include entrepreneurship, wage work, and non-employment.[32] In the regressions, the dependent variable is defined as "the number of people in a given labour market state in 2008 who were in a different labour market state in 1999," normalised by the baseline number of employed people in the province, thus allowing me to decompose the change in entrepreneurs described in Equation 2 into inflows and outflows.[33]

Table 7 decomposes the impact of immigration on entrepreneurship into inflows and outflows to and from other labour market states. The first column provides the increase in entrepreneurship, which is the same as in Column (3) from Table 5, for reference. Columns (2) to (4) refer to inflows and columns (5) to (7) refer to outflows. Column (3) shows the main contributor to the increase in entrepreneurship, namely, flows from wage work to entrepreneurship. Comparing inflows to outflows in Panel A shows that most of the effect is driven by inflows, and in particular inflows from wage work. Therefore, the entrepreneurship effect is driven by people who were entrepreneurs in 2008 but wage workers in 1999. However, when zooming across entrepreneur types in Panels B and C, there is a decrease in inflows from non-employment to unincorporated entrepreneurship and a similar sized, but positive, effect on flows from non-employment to incorporated

[32] Additionally, I consider transitions from entrepreneurship across local industries to achieve an exact decomposition of the total entrepreneurship effect.

[33] For instance, the change in the number of entrepreneurs between 1999 and 2008 can be decomposed into people who were entrepreneurs in 2008 but not in 1999 minus people who were entrepreneurs in 1999 but not in 2008 in a given local industry.

entrepreneurship. Non-employment represents an amalgamation of people working informally, studying, long-term unemployed or out of the labour force. Thus, I make no further claims on what is the driver behind these effects and I focus on flows from wage work to entrepreneurship in the rest of this section.

Since most of the inflows into entrepreneurship are driven by transitions from wage work, I can characterise who are these new entrepreneurs by analysing their baseline characteristics when they were wage workers. For this endeavour, I take two defining characteristics that the data include: baseline wages and occupational skill. Occupational skill is a 13-category variable reported by employers and used by the Social Security system to classify employees into skill levels.[34]

To divide workers by wages, I take quartiles of wages at the industry level at baseline and classify workers according to the quartile in which they belong. Therefore, I classify people who are entrepreneurs in 2008 according to their position in the wage distribution in 1999. In Table 8, I provide the results on flows from wage work to entrepreneurship by quartiles of baseline wages. Overall, 75% of the impact of immigration on native entrepreneurship is accounted by entrepreneurs who were in the top half of the baseline distribution within their industry.

Finally, in Table 9, I show that most of the effect is explained by workers in medium to high skilled occupations. Since wages and occupational skill are positively correlated, the results are similar to those for the wage distribution: 68% of the impact of immigration on native entrepreneurship is accounted by entrepreneurs who were in medium and high skill occupations in 1999.

Flows across local industries. An important driver of adjustment to immigration is flows across local labour markets (Dustmann et al., 2017). Therefore, in this section I decompose the entrepreneurship estimate from Table 5 into inflows and outflows across space. Since industry is only defined for people who are employed, I analyse transitions only amongst people who are employed in both 1999 and 2008.

Table 10 provides the results of the impact of immigration on inflows and outflows to and from entrepreneurship. On net, the increase in entrepreneurship is driven by inflows of wage workers into entrepreneurship, as documented in the previous subsection. When looking at the spatial origin, around 75% of new entrepreneurs reacting to the immigrant increase were previously wage workers in the same local industry, as shown by the coefficient in Column (2). The rest of new entrepreneurs were wage workers in other industries

[34] As occupations grow in skill requirement, the minimum and maximum Social Security contribution cutoffs increase. Hence, as occupational skill increases, minimum contributions to Social Security increase.

within the same province[35], as shown by Column (3). The impact of immigration on outflows across space is minimal.

3.4 Robustness

I begin the robustness checks by analysing the sensitivity of the main results in Table 5. I provide a battery of robustness checks in Table B1. First, in Panels A, B and C, I drop either Barcelona, Madrid or both. The results remain mostly unchanged, although power decreases and relevance of the first stage as well, although it still is above the $F > 10$ rule of thumb. In Panel D, I drop the agriculture industry as this industry is known for employing large rates of self-employed, almost exclusively natives, which typically employ many seasonal immigrant workers informally (Hoggart and Mendoza, 1999). The presence of agricultural sector, in which large numbers of informal immigrants working for low wages enables potential profits of entrepreneurs to raise, contributes directly to the argument proposed in this paper. However, its omission does not change the results. Then, in Panel E I confirm estimates are not driven by outliers in the dependent variable, as dropping the top and bottom 5 percent of observations does not yield different results.

I show that the results are robust to other specifications in which I do not normalise the outcome variable by employment in the province, or the explanatory variable by baseline working-age population in the province. In Panel F, I normalise the outcome variable by local industry employment rather than province employment. The estimates get larger and slightly noisier, as some local industries have quite small numbers of employed people in 1999, but the main results hold. Then, in Panel G I also normalise the independent variable, the immigration episode, by local industry imputed working age population. However, this measure becomes noisier and the first stage of the IV procedure becomes insignificant, leading to weak instrument bias, even if excluding outliers. Instead, I use OLS and I drop the top 10% provinces in terms of the shock, for which the immigration episode variable becomes unreasonably large. These are the local industries for which pre-existing baseline working age population is small, thus leading to a immigrant expansion of baseline population by more than 45 percentage points (up to 177pp for the largest outlier). When dropping outliers, the results are qualitatively similar to the OLS results in Panel B of Table 5. Finally, Panel H provides estimates without weighting by baseline population. All results survive qualitatively, although with a smaller magnitude, except for wages where the effect becomes negative and significant but only at the 15% significance level.

[35]The coefficient from Panel A Column (2) from Table 7 confirms that these individuals were indeed wage workers at baseline.

To show that the result holds even without aggregating the outcome across local industries, in Table B2, I run the regression at the individual level, focusing on transitions to and from entrepreneurship. In this case, I find that an increase in immigration at the local industry level is associated with an inflow of entrepreneurs, mostly incorporated, while there is no effect on entrepreneur outflows.

Another concern of this period is that the effect may be driven by other factors happening during this years in Spain. This could be the case of the 2005 regularisation, in which 600,000 immigrants obtained legal status with aid of a local employer (Elias et al., 2022). The regularisation could have raised artificially the number of native entrepreneurs, as natives may have registered as entrepreneurs just to aid the regularisation process of immigrants. In Figure B1 I show that the dynamic effect of the immigration episode increases steadily over the period. The pattern of coefficients shows that the effect built up over time and stayed positive even beyond my period of analysis. If the entrepreneurship effect had spiked in 2006 after the normalisation, this would otherwise mean that the regularisation could be driving the effect. The figure confirms this is not the case.

4 A Model of Occupational Choice and Immigration

4.1 Motivation for the Model

The empirical evidence shows that immigration increases native entrepreneurship, with limited effects on native wages or employment within a local industry. To interpret these findings, I focus on two competing mechanisms through which immigration can influence occupational choice.

First, immigration may increase entrepreneurial profits by lowering labour costs. Immigrants tend to work in low-wage jobs, and thus an immigrant-induced labour supply can raise the profitability of running a business.

Second, immigration may impact native wages, which alters the opportunity cost of entrepreneurship. If immigration depresses native wages due to increased competition, entrepreneurship becomes more attractive. Conversely, if immigrants complement natives in production, the incentives to remain in wage employment increase. The effect ultimately depends on the elasticity of substitution between immigrant and native labour, as well as the natives' elasticity of labour supply (Dustmann et al., 2017).

To analyse these mechanisms, I develop a stylised model of occupational choice and factor demand. The model integrates a Lucas-style entrepreneurial decision (Lucas, 1978) into a canonical labour demand framework (Wagner, 2010; Dustmann et al., 2017). In the

model, natives choose between wage work and entrepreneurship depending on which option offers a larger return. The model is useful to understand the relative role of native wage changes and input cost reductions in determining entrepreneurial choice, as well as entrepreneurial selection and who becomes a business owner.

To simplify the setting, the model considers only one local industry. The empirical results show this is not a far-fetched assumption. Almost 75% of new entrepreneurs were previously wage workers in the same industry, as shown in Section 3.3. Additionally, as shown in Table B7, net flows of native wage workers across industries are limited. These two results, together, suggest that occupational choices are influenced by changes in labour markets within local industries. The model should therefore be interpreted as a stylised but informative framework to interpret the main empirical results.

4.2 The Model

Set-up. Native individuals can choose whether to be wage workers or entrepreneurs, depending on the value V of each choice. Natives draw their ability z from a distribution with pdf f. Ability can be thought of as skill differences or differing labour supply endowments across individuals. If a native decides to become a wage worker, their labour earnings V_{WW} are equal to the wage rate for natives, w_N, times their ability z:

$$V_{WW} = z w_N$$

If a native decides to become an entrepreneur, they employ $n(z)$ and $i(z)$ units of effective native and immigrant labour, to produce an output $Q(z)$ that depends on their ability z:

$$Q(z) = z\left[a i(z)^{\rho} + n(z)^{\rho}\right]^{\frac{\alpha}{\rho}} = zL(z)$$

where a is the relative efficiency of immigrants with respect to natives. Then, $\alpha < 1$ is a decreasing returns to scale parameter, as in Lucas (1978). The substitution parameter ρ governs the degree of substitution/complementarity between native and immigrant workers.[36]

A large literature in immigration economics tries to obtain estimates of ρ.[37] However, existing estimates of ρ are calculated in settings where constant returns to scale (CRS) are assumed, i.e. $\alpha = 1$. Under CRS, $\rho \to 1$ implies that an immigrants and natives are

[36] Modelling production using as inputs immigrants and natives in only one nest of the CES function is not new. For instance, Mahajan (2024) uses the same production function, although with constant returns to scale ($\alpha = 1$) instead of decreasing returns to scale ($\alpha < 1$).

[37] Ottaviano and Peri (2012) and Manacorda et al. (2012) are two prominent examples.

substitutes in employment, i.e. an increase in immigration lowers native wages. Instead, if $\rho < 1$, an increase in immigration increases native wages.

In the presence of decreasing returns to scale, the values of ρ that make natives and immigrants substitutes or complements in employment are different. Complementarity in employment between immigrants and natives arises when $\rho < \alpha$. I don't make any prior assumption on whether natives and immigrants are substitutes or complements, and thus on the value of ρ.

The value of being an entrepreneur will be equal to the profit $\pi(z)$. Entrepreneurial profits are calculated as output $zL(z)$ minus labour costs, where the latter are defined as the number of natives and immigrants they hire times their wages, w_N and w_I, respectively. Therefore, the value of entrepreneurship is given by:

$$V_{EN}(z) = \pi(z) = zL(z) - w_I i(z) - w_N n(z)$$

In consequence, ability z determines both V_{EN} and V_{WW}. Higher z will lead to higher entrepreneurial profits and labour earnings, so the model inherently assumes that more skilled entrepreneurs are also more skilled workers, consistently with previous results in the entrepreneurship literature (Levine and Rubinstein, 2016). In Appendix D, I relax this assumption by extending the model and allowing for two different education levels. The extended model can endogenously create a positive correlation between average ability z and wages across education levels.

Finally, I assume immigrants can only work and supply one unit of labour inelastically in exchange for their wage w_I.

Equilibrium. An equilibrium of this economy consists of wage rates w_I and w_N, and an allocation of agents, such that taking wages as given, entrepreneurs demand inputs optimally, natives choose optimally between employment and entrepreneurship, and the labour market clears.

The first order conditions allow entrepreneurs to choose $n(z)$ and $i(z)$ optimally, taking wages as given:

$$w_I = z\alpha \left[ai(z)^\rho + h(z)^\rho\right]^{\frac{\alpha-\rho}{\rho}} ai(z)^{\rho-1} \tag{6}$$

$$w_N = z\alpha \left[ai(z)^\rho + h(z)^\rho\right]^{\frac{\alpha-\rho}{\rho}} h(z)^{\rho-1} \tag{7}$$

Wages are determined in equilibrium by optimal the occupation choice condition and labour market clearing. The optimal occupational choice condition defines a cutoff z^*, for which natives with $z > z^*$ become entrepreneurs, and the rest become wage workers.

Hence, z^* represents the ability of the marginal entrepreneur that is indifferent between being a wage worker or entrepreneur:

$$V_{WW}(z^*) = V_{EN}(z^*) \iff z^* w_N = \pi(z^*) \tag{8}$$

Finally, to close the model, the labour supply of immigrants and natives must be equal to their demand by entrepreneurs. Labour supply by natives is given by LS_N, which is determined endogenously. Labour supply for immigrants is given by LS^I, which is exogenous as they do not own firms and supply their labour inelastically. Let $f(z)$ be the pdf of z. Then, labour market clearing conditions can be written as follows:

$$LS_N = \int_{z^*} f(z) n(z) dz \tag{9}$$

$$LS_I = \int_{z^*} f(z) i(z) dz \tag{10}$$

Comparison to previous literature. Most of the literature on the impact of immigration on natives' labour market outcomes has focused on the impact on native wages (Dustmann et al., 2016). The main channel through which immigration impacts natives' wages is through substitutability or complementarity in production, typically modelled using a CES production function combining immigrants and natives in ways that differ across studies (Wagner, 2010; Dustmann et al., 2016). By adding the entrepreneurship option amongst natives to the factor demand model, two additional mechanisms affecting wages arise. First, entrepreneur selection will impact average wages: if more natives become entrepreneurs, the productivity cut-off z^* decreases, thus depressing wages due to negative selection of less productive entrepreneurs. Second, relative quantities of workers will also impact wages. For instance, if more native workers become entrepreneurs, there will be relatively less native workers, thus pushing their price up.

Calibration. I calibrate the model by finding parameters that reduce the distance between model moments and empirical moments.[38] First, I set externally $\alpha = 0.9$, to obtain a profit share of income of 10%.[39] Then, I suppose z follows a log-normal distribution with mean μ_z and variance σ_z^2. Second, I internally calibrate the remaining parameters of the model, $\theta = \{\rho, a, \mu_z, \sigma_z^2\}$, by minimising the distance between data moments and moments simulated by the model.

To discipline the model, I use both baseline moments and dynamic moments. For base-

[38] For more details on the calibration, see Appendix D.1.

[39] I use the same α as Poschke (2018).

line moments, I use the native entrepreneur share and wages of natives relative to immigrants, obtained directly from descriptive statistics of the data in 1999, before the immigration episode. Dynamic moments include the increases in wages and entrepreneurship for natives, calculated using the treatment effects identified in the empirical section, i.e. the $\hat{\beta}$ estimates from Table 5. To calibrate the model, I simulate the model both with the share of immigrants before and after the immigration episode[40], calculate baseline and dynamic moments, and find the parameters that minimise the objective function that combines the distances between data and model moments.

Table 11 presents the results of the calibration. The model moments closely match the data moments. The calibrated parameters are reasonable when interpreted through the lens of previous research. The substitution parameter $\rho = 0.46$ implies complementarity in employment, as an increase in immigration leads to an increase in the marginal product of natives.[41] This is consistent with previous literature documenting that labour demand of natives can increase due to complementarities in production between natives and immigrants (Peri and Sparber, 2009; Manacorda et al., 2012; Beerli et al., 2021). Then, $a = 0.03$ shows that immigrants are less productive than natives, consistent with the patterns shown in Section 1.1. The parameters μ_z and σ_z^2 characterise the ability distribution for natives.[42]

Finally, the model predicts that immigrant wages in 2008 are 35% of its real value in 1999. This large decrease is a direct consequence of assuming inelastic labour supply among immigrants. However, it is difficult to gauge how far off this moment is. This is because reliable data on immigrant wages is hard to come by, specially when considering their larger participation in the informal sector. In Appendix C, I discuss supporting evidence showing that immigrant wages decreased both in real terms and when compared to natives during this period. However, the decrease predicted by the model, while correct in direction, is definitely an overestimate of the actual magnitude of the immigrant wages decrease.

4.3 Counterfactual Decomposition of the Entrepreneurship Increase

In this section, I perform a counterfactual decomposition of the effect of immigration on native entrepreneurship. This exercise is aimed at isolating how much the impact of immi-

[40] These are obtained from the average immigrant shares across local industries, namely 2.14% in 1999 and 14% in 2008.

[41] Since $\rho = 0.46 < 0.9 = \alpha$, we have that $\frac{\partial w_N}{\partial i(z)} > 0$ using the first order condition from Equation 7.

[42] The distribution has positive support, and plotting V_{WW} and V_{EN} shows that there is single crossing, i.e., only one z^*.

gration on (i) native wages or on (ii) potential profits is driving the native entrepreneurship increase. This exercise indicates which mechanism, on average, is more likely to explain the increase in entrepreneurship.

To obtain intuition about this exercise, Figure 6 shows how occupational choice operates in the model. Panel (a) shows how the payoffs of entrepreneurship, $V_{EN}(z) = \pi(z)$, and wage work, $V_{WW}(z) = zw_N$, vary with ability z. The intersection of these curves, namely z_1^*, defines a cut-off above which all individuals with $z \in [z_1^*, z_{max}]$ become entrepreneurs, and all other individuals with $z \in [z_{min}, z_1^*)$ become wage workers. In the model, the optimal occupational choice condition in Equation 8 determines z^*. Panel (b) shows how the impact of immigration on native wages affects occupational choice. An increase in native wages due to complementarity in production between natives and immigrants pushes z^* up to z_2^*. Therefore, all natives with $z \in [z_1^*, z_2^*]$ become wage workers with respect to the baseline equilibrium. Panel (c) illustrates how the increase in potential profits, which arises due to the decrease in immigrant wages stemming from the immigrant labour supply expansion and perfect substitutability among immigrants, impacts occupational choice. The profit curve shifts up, and the new cut-off z_3^* indicates that, with respect to the baseline equilibrium, all native wage workers with $z \in [z_3^*, z_1^*]$ become entrepreneurs. Since in equilibrium shifts in both V_{WW} and V_{EN} happen simultaneously, it is not possible to immediately recover the impact of each channel.

To decompose the contribution of each channel, I simulate the calibrated model in the post immigration episode (2008) period but fixing either potential profits or native wages at baseline (1999) in the occupational choice condition. This is equivalent to estimating the model fixing either the right-hand side or left-hand side parts of Equation 8 to baseline, respectively. The resulting equilibria show how occupational choice depends on either the impact of immigration on native wages or on potential profits, respectively.

Post-immigration equilibrium. The first column of Table 12 shows the result of increasing immigration without decomposing the effect. The increase in entrepreneurship among natives despite higher wages suggests that the impact of immigration on potential profits dominates the impact on native wages. However, the native wage effect combines the impact of immigration through complementarity in the labour market with the impact on entrepreneurial selection and relative quantities. To isolate how much increased profits or increased native wages are driving changes native in entrepreneurship, I now turn to the counterfactual scenarios.

Counterfactual: occupational choice depends only on native wages. The second column of Table 12 provides the results of this counterfactual. Keeping potential profits fixed

at baseline, without the immigration increase, makes natives' labour supply choices depend only on wage changes induced by the immigrant labour supply shock. Wages of natives increase with respect to the original post immigration episode in the first column. This increase suggests that positive entrepreneur selection–i.e. only the most productive entrepreneurs remain entrepreneurs–compensates the negative impact on native wages of a higher supply of native workers. Consequently, when comparing to the first column, both the opportunity cost of entrepreneurship, i.e. native wages, and the cost of entrepreneurship, i.e. native and immigrant wages, increase, thus lowering entrepreneurship with respect to the original scenario.

Counterfactual: occupational choice depends only on potential profits. The third column of Table 12 provides the results of this counterfactual. When native wages are fixed at baseline upon conditional choice, native occupational choices are driven by changes in potential profits. Since immigrants are perfect substitutes among themselves, an increase in immigration depresses immigrant wages. In turn, the potential profits curve shifts up for natives. Entrepreneurship increases sharply, lowering the relative amount of native wage workers but lowering average ability of existing entrepreneurs. On net, natives' wages increase slightly, while negative entrepreneur selection pushes down further wages of immigrants.

Taken together, the last two counterfactual scenarios suggest that the increase in profits due to immigrants' lower wages is the main channel behind the increase in native entrepreneurship, as the shift in the potential profits curve drives the increase in entrepreneurship. Finally, the decomposition is not exact, although precise. This is a consequence of altering only the optimal occupational choice equation in the counterfactual simulations, but not the labour market clearing conditions.

The increase in native entrepreneurship due to immigrants lowering labour costs is consistent with the empirical results. One of the main testable predictions of the model is that the new entrepreneurs are those who, absent the immigration shock, would be wage workers with relatively higher entrepreneurial ability z amongst all wage workers. This is consistent with the empirical evidence on flows obtained in Section 3.3, as those natives who are more likely to be entrepreneurs by the end of the immigration shock are those who at baseline were in better occupations and earning higher wages. Additional evidence in favour of this view is given by the fact that most of the effect is explained by incorporated entrepreneurs, which are more likely to hire than unincorporated entrepreneurs[43] and are

[43]This is according to official statistics (INE, 2008), but it is likely that many entrepreneurs hired immigrants informally as the informal sector increased during this period (Bosch and Farré, 2014) and probability of detection by government is lower for smaller businesses (Ulyssea, 2018).

typically thought to be higher-quality ventures (Levine and Rubinstein, 2016). Finally, in Appendix D I show these insights remain unchanged when expanding the model to include two levels of education amongst natives.

Modelling entrepreneurship and, more generally, the employer productivity distribution, enhances our understanding of the labour market impact of immigration. In my setting, immigration fosters the entry of new entrepreneurs that lower average employer productivity, negatively impacting wages. Therefore, if entrepreneurial responses exist and are not taken into account, the impact of immigrant supply on native wages can be negatively biased. In terms of the impact of immigration on native employment, if entrepreneurs were dropped from the analysis or counted as non-employed, the employment impact of immigration could also negatively biased. More generally, entrepreneurship responses can be another factor mediating the impact of immigration on native wages and employment. Importantly, this mechanism is setting dependent. For instance, in an scenario where only larger, more productive firms, can afford to hire immigrants (Brinatti and Morales, 2023; Mahajan, 2024), not acknowledging impacts on the employer productivity distribution may actually overestimate the wage impact of immigration, as positive employer selection may drive the wage effect rather than labour market complementarity.

4.4 Policy Experimentation

The evidence presented so far is consistent with a positive impact on native labour markets due to immigration. Despite a large literature showing mostly a null or slightly positive impact of immigration on native labour markets (Edo, 2019), there has been a sustained political backlash against immigration in recent years. Across Europe, immigration, specifically from low income countries, is associated with a switch toward more nationalistic and right-wing parties (Moriconi et al., 2022). While this backlash is also present in Spain, it was relatively modest during the period of analysis (Mendez and Cutillas, 2014).

One of the main demands of immigration opposers is to reduce immigration, and particularly undocumented immigration. Many of the policies used to reduce (undocumented) immigration are usually associated with increased labour costs (Chassamboulli and Peri, 2015). While previous research has investigated these policies, none of the models consider firm entry, and in particular, occupational choice, in their studies. In this subsection, I investigate how a policy raising labour costs associated with hiring immigrants impacts natives' labour market outcomes, in presence of an entrepreneurship option amongst natives.

Consider the introduction of a minimum wage which is binding for immigrants. I set

this minimum wage equal to pre-episode immigrant wages. In this experiment, an increase in immigration does not reduce wages of immigrants, as minimum wages are binding. Table 13 shows the impact of such a minimum wage policy. Column (1) compares the evolution of entrepreneurship, wages, and average native income in the original scenario, while Column (2) compares these statistics but with immigrant wages facing a binding minimum wage. Under the minimum wage, the number of entrepreneurs decreases with respect to baseline, as not all existing entrepreneurs can face the labour costs associated with an increase in immigrant wages.

A priori, a decrease in entrepreneurship has an ambiguous effect on native wages. Positive selection drives up wages, while a larger pool of workers puts downward pressure on wages. In this case, the former dominates, with native wages increasing in the presence of a minimum wage for immigrants, thus benefitting native workers. However, the increase in labour costs lowers entrepreneurial income for all entrepreneurs. To understand how average income of natives changes, I calculate the percentage change in average income with respect to the baseline scenario. Immigration unambiguously increases average native income, regardless of whether there is a minimum wage or not. However, minimum wages redistribute some of the gains of an expanded economy from entrepreneurs to immigrants, and hence average native income is counterfactually lower in the presence of a binding minimum wage for immigrants.

Therefore, higher labour costs reduce average native income, but with distributional consequences. Non-marginal workers, those who work regardless of the scenario, benefit from higher wages in the presence of a tax, due to positive entrepreneur selection. Entrepreneurs are the most affected by higher labour costs. But compared to baseline, immigration still has a widespread positive impact, due to formalisation costs positively selecting entrepreneurs, and complementarity in the labour market between immigrants and natives.

5 Conclusion

I provide evidence on the positive effect of immigration on native entrepreneurship, using Spain as a case study. Immigration episodes in developed economies have been pervasive in recent history, and the number of international immigrants in developed economies has only grown. Still, there is a widespread belief that immigrants might be an economic burden, and particularly, might have negative consequences on labour market outcomes of natives. In this paper I focus on one of the largest immigration episodes in the post-war era among OECD countries, and I argue that international immigration fosters native

entrepreneurship, while having a limited impact on employment and wages of natives. More concretely, my main contribution is to show that these immigration episodes can foster the entry to entrepreneurship among natives. This is plausibly explained by immigration lowering labour costs. This effect is stronger for individuals with relatively higher entrepreneurial ability and whose businesses would´t be profitable in absence of the immigration episode.

While a decrease in labour costs due to immigration is likely to be an important driver of the increase in entrepreneurship, it is likely not the only factor at play. Three other mechanisms can coexist. First, immigrant consumption may also play a role, although I try to abstract as much as possible by focusing on the labour supply shock by leveraging local industry variation. Also, since immigrants tend to send remittances and consume in the country of origin (Albert and Monras, 2018), its impact on local consumption may not be substantial. Second, immigrant entrepreneurs may complement native entrepreneurs. In Table B6 I show there's a positive, yet an order of magnitude smaller, increase in immigrant entrepreneurship. This finding is consistent with descriptive evidence showing that immigrants in Spain, while perceiving more business opportunities than natives, are less likely to exploit them (Bolívar-Cruz et al., 2014). This phenomena can be explained by immigrants facing higher legal and institutional problems when starting a business, as well as having larger credit constraints and lower entrepreneurial capital than natives. In consequence, I do not explore this channel. Third, some natives may actually be displaced (Castellanos, 2024) and start firms out of necessity, although the contribution of this margin seems to be limited.

Finally, the results in my paper depend crucially on immigrant composition. Immigrants who entered Spain during the analysis period mostly worked in low-paying manual jobs. In other countries, such as the US in the present century, immigrants represent a high share in skilled occupations (Kerr et al., 2015) and have higher rates of entrepreneurship than natives (Kerr and Mandorff, 2023). Consistently, the impact of immigration on the count of native owned business has recently been found to be negative in the US (Mahajan, 2024). Contrary to this, in my setting, as immigrants lower labour costs but do not generally compete with native entrepreneurs, immigration has a positive impact on native entrepreneurship. Hence, my findings relate more directly to scenarios in which immigrants suffer substantial occupational downgrading or mostly take low-wage jobs, such as refugee episodes (Altindag et al., 2020), or developing to developed countries immigration episodes, such as the literature on H2B visas in the US (Clemens and Lewis, 2024; Amuedo-Dorantes et al., 2024).

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Tables

Table 1: Comparison of labour market outcomes between natives and immigrants

	Natives	Immigrants
Total	651,222	86,562
Share male	0.57	0.61
Average age	39.17	35.52
Average tenure	5.59	1.87
Average daily wage	64.0	43.9
Occupation shares		
Low skill	0.45	0.74
Medium skill	0.35	0.19
High skill	0.20	0.06
Entrepreneurs		
Self-employed	0.17	0.11
Unincorporated	0.12	0.09
Incorporated	0.05	0.02
Industry		
Agriculture	0.02	0.06
Manufacturing	0.16	0.18
Construction	0.11	0.19
Hospitality and retail	0.24	0.25
Other services	0.47	0.32

Note: This table provides a comparison of natives and immigrants in the year 2008 using data from the MCVL. The data correspond to individuals aged 20 to 60. Daily wages are calculated in euros and are total yearly earnings divided by the number of days worked, among full-time wage workers who were employed all year long. Skills are calculated using occupations, which in the MCVL data correspond to skill levels as viewed by the employer.

Table 2: Native labour market outcomes, analysis sample

	1999	2008
Total	466,925	466,925
Wage Workers	279,874	333,288
Entrepreneurs	38,991	72,506
Unincorporated	27,047	47,349
Incorporated	11,944	25,157
Average age	32.2	40.4
Average tenure	4.2	6.4
Average wage	44.0	49.5
Education		
Low education	214,786	214,786
High education	252,139	252,139
Occupation (*wage workers*)		
Low skill	97,846	129,708
Medium skill	84,302	87,998
High skill	52,526	39,800
Industry (*wage workers*)		
Agriculture	2,276	2,833
Manufacturing	57,396	57,155
Construction	29,743	30,122
Hospitality and retail	67,109	69,041
Other services	123,350	174,137
Industry (*entrepreneurs*)		
Agriculture	4,501	6,096
Manufacturing	4,166	6,564
Construction	5,168	11,565
Hospitality and retail	14,668	25,254
Other services	10,488	23,027

Note: This table provides information on the analysis sample, splitting by year. All statistics are counts, except for average age, tenure and wage. Age and tenure are expressed in years, while average wage is expressed in daily wages among full-time wage workers who were employed during the whole year. Skills are calculated using occupations, which in the MCVL data correspond to skill levels as viewed by the employer. Low education refers to less than secondary, medium to secondary education, and high to more than secondary.

Table 3: Descriptive statistics of the main variables

	Mean	Std. Dev.	Max	Min
Main variables				
Change Native Entrepreners (normalised)	0.029	0.014	0.064	-0.001
Change Native Unincorporated Entr. (normalised)	0.018	0.010	0.055	-0.000
Change Native Incorporated Entr. (normalised)	0.012	0.005	0.030	-0.001
Change Native Wage Workers (normalised)	0.068	0.085	0.262	-0.070
Change Log Wages	0.004	0.042	0.617	-0.360
Immigration Episode	0.044	0.030	0.115	-0.000

Note: The table presents descriptive statistics for the main variables used in the analysis, using the analysis sample, that is, using the data aggregated across 250 local industries, from data on natives born between 1954 and 1979, as explained in Section 1. The first four variables follow Equation 2 and are the changes in number of native entrepreneurs, unincorporated and incorporated and wage workers between 1999 and 2008 across local industries, normalised by the province native employment (equal to the sum of the province native wage workers and native entrepreneurs) in 1999. The difference in log wages is calculated from 1999 to 2008, and log wages are obtained as residuals from a regression of log daily wages on quadratic age and tenure profiles, and occupational skill and year fixed effects, using wages only from wage workers. The immigration episode corresponds to Equation 1 and represents the change in a local industry immigrant population over the province baseline working age population.

Table 4: First stage

	Outcome: ΔImmigration Shock$_{ip}$			
	(1)	(2)	(3)	(4)
$\Delta\widehat{\text{Immigration}}$ Shock$_{ip}$	0.603***	0.447***	0.610***	0.472***
	(0.04)	(0.09)	(0.07)	(0.10)
Controls		X		X
Industry/Province FE			X	X
F-statistic	210.61	26.67	67.24	23.11
Observations	250	250	250	250

Note: This table presents first-stage regressions of the immigrant episode on the instrument, as explained in Section 2. The F-statistic corresponds to the F-statistic on the excluded instrument, namely the predicted immigration episode. Observations are weighted by baseline employment in each local industry. Robust standard errors are reported in parenthesis. Significance levels: $^{+}p < 0.15, ^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 5: Entrepreneurship, Employment and Wage effects of immigration

	(1) Δ Employment	(2) Δ Wage Workers	(3) Δ Entrepreneurs	(4) Δ Unincorporated	(5) Δ Incorporated	(6) Δ Wage
Panel A: OLS, no controls						
Δ Immigration Shock	0.269	0.026	0.243***	0.129***	0.114***	0.003
	(0.22)	(0.20)	(0.05)	(0.04)	(0.02)	(0.02)
Panel B: OLS, with controls						
Δ Immigration Shock	0.159	-0.052	0.211***	0.113***	0.098***	0.009
	(0.18)	(0.18)	(0.04)	(0.03)	(0.02)	(0.02)
Panel C: 2SLS, without controls						
Δ Immigration Shock	0.375^{+}	0.062	0.314***	0.145***	0.169***	0.013
	(0.25)	(0.22)	(0.07)	(0.05)	(0.02)	(0.02)
First-stage KP	67.24	67.24	67.24	67.24	67.24	67.24
Panel D: 2SLS, with controls						
Δ Immigration Shock	0.132	-0.100	0.232***	0.051	0.181***	0.058*
	(0.30)	(0.29)	(0.06)	(0.05)	(0.03)	(0.03)
First-stage KP	23.11	23.11	23.11	23.11	23.11	23.11
Baseline workforce share		0.878	0.122	0.085	0.037	
Mean dep. var	9.79	6.84	2.94	1.79	1.15	0.04
Observations	250	250	250	250	250	250

Note: This table provides the estimates from estimating β from Equation 3 using either OLS or IV, and adding or not controls. Each column corresponds to an outcome, namely, a difference in the number of native individuals in a given occupational category from 1999 to 2008 in a local industry normalised by baseline province employment for Columns (1) to (5), and to the change in log wages during the same period in Column (6). Additional information on the outcome variables, the immigration episode, or the specification is in Sections 1 and 2. Robust standard errors are provided in parenthesis. Observations are weighted by baseline local industry employment. The Table provides the mean of each dependent variable in percentage terms (multiplied by 100), as well as baseline shares of each employment category in Columns (2) to (5). Finally, I provide first-stage Kleibergen-Paap rk Wald F statistics and the total number of observations used in the estimation. Significance levels: $^{+}p < 0.15,^{*} p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table 6: Entrepreneurship, Employment and wage effects of immigration, by education

	(1) Δ Employment	(2) Δ Wage Workers	(3) Δ Entrepreneurs	(4) Δ Unincorporated	(5) Δ Incorporated	(6) Δ Wage
Panel A: High education						
Δ Immigration Shock	0.053	-0.142	0.195***	0.064**	0.130***	-0.422
	(0.24)	(0.22)	(0.04)	(0.03)	(0.02)	(0.46)
Panel B: Low education						
Δ Immigration Shock	0.079	0.041	0.038	-0.013	0.051***	1.364***
	(0.15)	(0.15)	(0.04)	(0.03)	(0.02)	(0.51)
First-stage KP	23.11	23.11	23.11	23.11	23.11	23.11
Observations	250	250	250	250	250	250

Note: This table provides the estimates from estimating β from Equation 3 using the migrant networks instrument detailed in Section 2 and controls. Panel A estimates results for high-education individuals, and Panel B for low-education individuals. Each column corresponds to an outcome, namely, a difference in the number of native individuals, by education, in a given occupational category from 1999 to 2008 in a local industry normalised by baseline province employment for Columns (1) to (5), and to the change in log wages for each education level during the same period in Column (6). Additional information on the outcome variables, the immigration episode, or the specification is in Sections 1 and 2. Robust standard errors are provided in parenthesis. Observations are weighted by baseline local industry employment. The Table provides the mean of each dependent variable in percentage terms (multiplied by 100). Finally, I provide first-stage Kleibergen-Paap rk Wald F statistics and the total number of observations used in the estimation. Significance levels: $^{+}p < 0.15, ^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 7: Flows to and from Entrepreneurship

		Inflows			Outflows		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Entrepreneurship	Entrepreneurship (Other LI)	Wage Work	Non-Employment	Entrepreneurship (Other LI)	Wage Work	Non-Employment
Panel A: All							
Δ Immigration Shock	0.232***	0.003	0.226***	0.004	-0.003	-0.003	0.005
	(0.06)	(0.00)	(0.04)	(0.04)	(0.00)	(0.01)	(0.00)
Mean dep. var	2.94	0.04	1.73	1.59	0.03	0.29	0.09
Panel B: Unincorporated							
Δ Immigration Shock	0.051	0.002	0.094***	-0.056^{+}	-0.001	-0.002	-0.003
	(0.05)	(0.00)	(0.03)	(0.04)	(0.00)	(0.01)	(0.01)
Mean dep. var	1.79	0.02	1.03	1.05	0.02	0.21	0.07
Panel C: Incorporated							
Δ Immigration Shock	0.181***	-0.001	0.132***	0.059***	0.001	-0.000	0.008***
	(0.03)	(0.00)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)
Mean dep. var	1.15	0.01	0.70	0.54	0.01	0.08	0.02
First-stage KP	23.11	23.11	23.11	23.11	23.11	23.11	23.11
Observations	250	250	250	250	250	250	250

Note: This table provides the estimates from estimating β from Equation 3 using the migrant networks instrument detailed in Section 2 and controls. Panel A estimates results for all entrepreneurs, while Panels B and C estimate results for unincorporated and incorporated entrepreneurs, respectively. Each column corresponds to an flow outcome, except Column (1), which corresponds to Column (3) from Table 5. Column (2) are flows from entrepreneurship in other local industries in 1999 to entrepreneurship in the local industry. Column (3) are flows from wage work in 1999 to entrepreneurship in 2008, and Column (4) likewise but from non-employment. Columns (5) to (7) are defined similarly, but as outflows. All flows are normalised by baseline employment in the province. Additional information the immigration episode or the specification is in Sections 1 and 2. Robust standard errors are provided in parenthesis. Observations are weighted by baseline local industry employment. The Table provides the mean of each dependent variable in percentage terms (multiplied by 100). Finally, I provide first-stage Kleibergen-Paap rk Wald F statistics and the total number of observations used in the estimation. Significance levels: $^{+}p < 0.15, ^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 8: Flows from Wage Work to Entrepreneurship by Baseline Wage Quartiles

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
Panel A: All				
Δ Immigration Shock	0.028^{+}	0.020	0.075***	0.103***
	(0.02)	(0.02)	(0.01)	(0.01)
Mean dep. var	0.59	0.44	0.34	0.36
Panel B: Unincorporated				
Δ Immigration Shock	0.012	-0.000	0.035***	0.047***
	(0.01)	(0.01)	(0.01)	(0.01)
Mean dep. var	0.38	0.27	0.19	0.19
Panel C: Incorporated				
Δ Immigration Shock	0.016**	0.020***	0.040***	0.056***
	(0.01)	(0.01)	(0.01)	(0.01)
Mean dep. var	0.21	0.17	0.15	0.17
First-stage KP	23.11	23.11	23.11	23.11
Observations	250	250	250	250

Note: This table provides the estimates from estimating β from Equation 3 using the migrant networks instrument detailed in Section 2 and controls. Panel A estimates results for all entrepreneurs, while Panels B and C estimate results for unincorporated and incorporated entrepreneurs, respectively. Each column corresponds to the number of people who were wage workers in a given quartile in of the wage distribution in 1999 but entrepreneurs in the local industry in 2008, and each is normalised by baseline employment in the province. Quartiles are calculated from distributions at the industry level. Additional information the immigration episode or the specification is in Sections 1 and 2. Robust standard errors are provided in parenthesis. Observations are weighted by baseline local industry employment. The Table provides the mean of each dependent variable in percentage terms (multiplied by 100). Finally, I provide first-stage Kleibergen-Paap rk Wald F statistics and the total number of observations used in the estimation. Significance levels: $^{+}p < 0.15$,* $p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

Table 9: Flows from Wage Work to Entrepreneurship by Baseline Occupations

	(1) LS occ.	(2) MS occ.	(3) HS occ.
Panel A: All			
Δ Immigration Shock	0.067**	0.106***	0.052***
	(0.03)	(0.02)	(0.01)
Mean dep. var	0.92	0.54	0.27
Panel B: Unincorporated			
Δ Immigration Shock	0.017	0.052***	0.025***
	(0.02)	(0.01)	(0.01)
Mean dep. var	0.59	0.30	0.14
Panel C: Incorporated			
Δ Immigration Shock	0.050***	0.054***	0.027***
	(0.02)	(0.01)	(0.01)
Mean dep. var	0.33	0.24	0.13
First-stage KP	23.11	23.11	23.11
Observations	250	250	250

Note: This table provides the estimates from estimating β from Equation 3 using the migrant networks instrument detailed in Section 2 and controls. Panel A estimates results for all entrepreneurs, while Panels B and C estimate results for unincorporated and incorporated entrepreneurs, respectively. Each column corresponds to the number of people who were wage workers in a given occupations in 1999 but entrepreneurs in the local industry in 2008, and each is normalised by baseline employment in the province. Additional information the immigration episode or the specification is in Sections 1 and 2. Robust standard errors are provided in parenthesis. Observations are weighted by baseline local industry employment. The Table provides the mean of each dependent variable in percentage terms (multiplied by 100). Finally, I provide first-stage Kleibergen-Paap rk Wald F statistics and the total number of observations used in the estimation. Significance levels: $^{+}p < 0.15,^{*} p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table 10: Entrepreneurship Flows across Local Industries

	(1) Net	(2) Same Local Industry	(3) Same Province Different Industry	(4) Different Province Same Industry	(5) Different Province Different Industry
Panel A: Inflows					
Δ Immigration Shock	0.227***	0.169***	0.067***	-0.003	-0.005
	(0.04)	(0.03)	(0.02)	(0.01)	(0.00)
Panel B: Outflows					
Δ Immigration Shock	-0.002	0.008	-0.009*	-0.001	-0.000
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
First-stage KP	23.11	23.11	23.11	23.11	23.11
Observations	250	250	250	250	250

Note: This table provides the estimates from estimating β from Equation 3 using the migrant networks instrument detailed in Section 2 and controls. Panel A estimates inflows into entrepreneurship, while Panel B estimates outflows. Inflows are defined as the number of people that were entrepreneurs in 2008 in a given local industry but not entrepreneurs in the same local industry in 1999 (Column 2), or alternatively they were in 1999 either wage workers or entrepreneurs in the same province but another industry (Column 3), in a different province but in the same industry (Column 4), and in a different province and industry (Column 5). Outflows are defined analogously. Additional information the immigration episode or the specification is in Sections 1 and 2. Robust standard errors are provided in parenthesis. Observations are weighted by baseline local industry employment. The Table provides the mean of each dependent variable in percentage terms (multiplied by 100). Finally, I provide first-stage Kleibergen-Paap rk Wald F statistics and the total number of observations used in the estimation. Significance levels: $^{+}p < 0.15$,* $p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

Table 11: Moments and parameters from model calibration

Moment	Data	Model
Baseline Entrepreneurship Rate	0.122	0.123
Δ Entrepreneurship (pp)	0.03	0.0297
Baseline $\frac{w_N}{w^I}$	1.22	1.21
Δw_N (%)	1.025	1.026

Parameter	Value
ρ	0.46
a	0.03
μ_z	1.46
σ_z^2	0.11

Note: The left table provides moments used in the estimation of the model of occupational choice and immigration laid out in Section 4.2. The right table provides the parameters and calibrated values. ρ is the substitution parameter for immigrants and natives. The parameter a is the relative productivity parameter of immigrants with respect to natives. The parameters μ_z and σ_z^2 are the mean and standard deviation of the log-normal distribution of entrepreneurial ability for natives.

Table 12: Counterfactual decomposition of the impact of immigration on native entrepreneurship

		Post immigration episode, occupational choice depends only on...	
Increase in:	Post immigration episode	Native Wages	Potential Profits
Entrepreneur Share (pp)	0.030	-0.006	0.031
Native Wages (%)	1.026	1.032	1.029
Immigrant Wages (%)	0.349	0.361	0.345

Note: The table displays key statistics for native entrepreneurs, and wages, under the counterfactual composition described in Section 4.3. Each column shows a different scenario, with respect to the quantities in the baseline period before the immigration episode. The first column shows the actual post immigration episode scenario. The second and third column show the equilibrium in the case when immigration impacts occupational choice either through native wages or native potential profits, respectively.

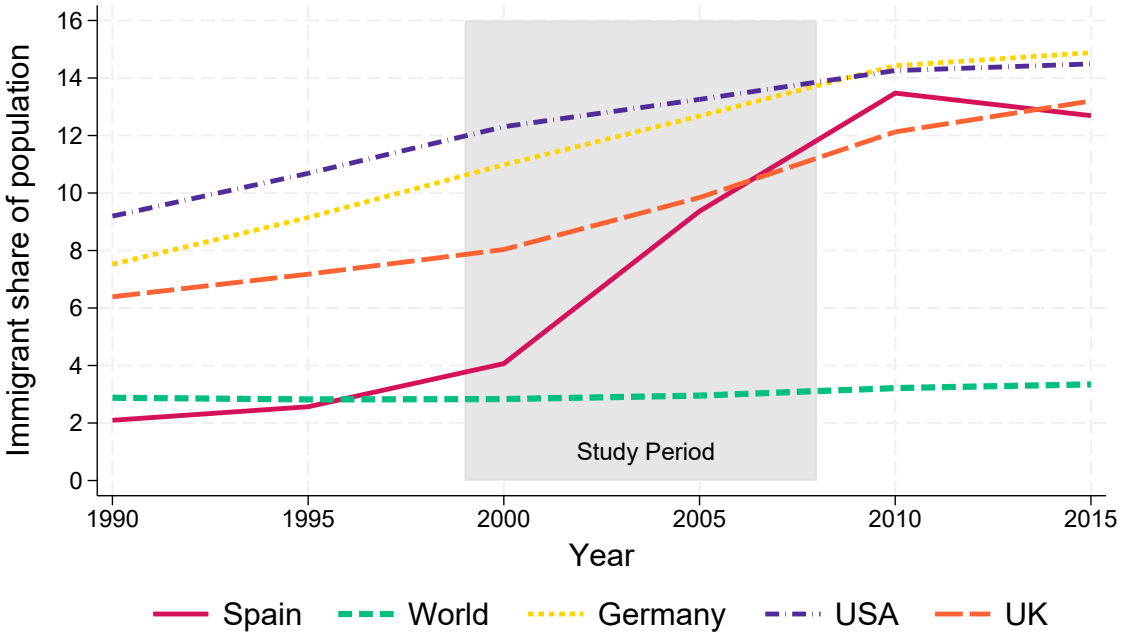
Table 13: Counterfactual experiment with binding minimum wage for immigrants

Increase in:	Post immigration episode	Post immigration episode, MW
Entrepreneur Share (pp)	0.030	-0.020
Native Wages (%)	1.026	1.039
Immigrant Wages (%)	0.349	1.000
Native Income (%)	1.039	1.029

Note: The table displays key statistics for native entrepreneurs, and wages, under the counterfactual composition described in Section 4.4. Each column shows a different scenario, with respect to the quantities in the baseline period before the immigration episode. The first column shows the actual post immigration episode scenario. The second column introduces a minimum wage for immigrants.

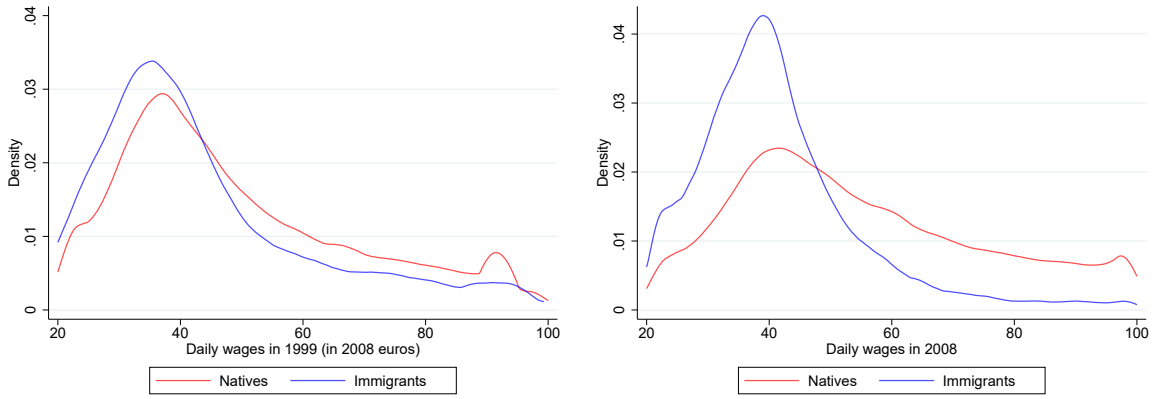
Figures

Figure 1: International comparison of immigrant shares



Note: The figure compares the evolution of the immigrant share of population in Spain with that of Germany, United Kingdom, the United States and the world average. Data come from the World Bank.

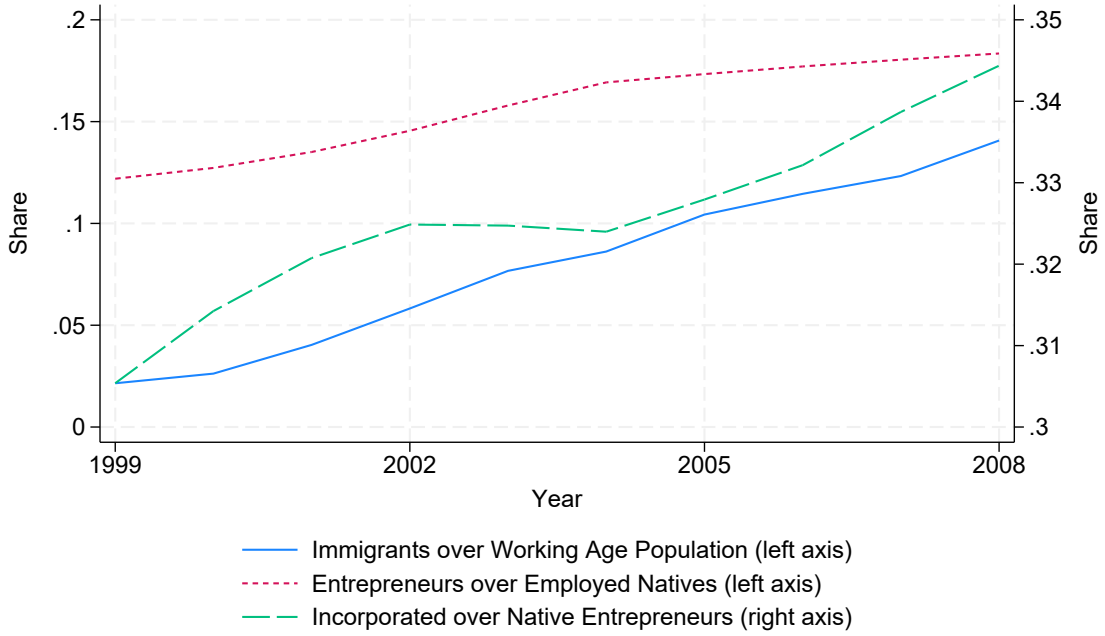
Figure 2: Wage distributions in 1999 and 2008, for natives and immigrants



(a) 1999 (b) 2008

Note: The figures plot kernel density estimations for wages among native males and females, and immigrants, using data for the years 1999 and 2008 from the MCVL. The data correspond to individuals born between 1954 and 1979 for natives, and immigrants aged 20 to 60 for each year. Daily wages are calculated in euros and are total yearly earnings divided by the number of days worked, among full-time wage workers who were employed all year long, as in Table 1.

Figure 3: Evolution of immigration and native entrepreneurship

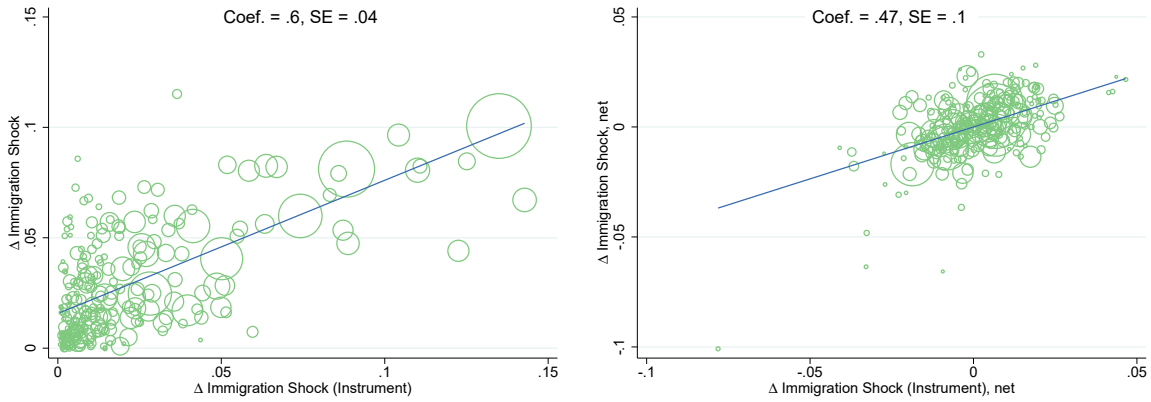


Note: The figure plots the evolution of different key statistics from 1999 to 2008. The solid line represents the evolution of immigrants over working age population (shares in left axis). The short-dash line represents the share of entrepreneurs over employed natives (shares in left axis). The long-dashed line represents the share of incorporated entrepreneurs over total entrepreneurs for natives (shares in right axis).

Figure 4: Conditional exogeneity of the instrument, reduced form

Note: The figure shows the reduced form impact of the instrument, defined in Section 2, on preperiod (red) and study period (blue) outcomes. The plot provides the coefficient (dots) and 95% confidence intervals. The specification is similar to Equation 3, but the explanatory variable is the instrument, instead of the realised immigration episode. Reduced-form regressions are weighted by baseline province employment (either 1990 or 1999). None of the preperiod and study period coefficients are statistically different, with the exception of the entrepreneurs (p-value equal to 0.001). Preperiod statistics are calculated for the 1954-1970 cohort, as later cohorts were likely not participating in the labour market in 1990. Wages are obtained as residuals from an individual level regression on age and tenure quadratic profiles by gender, occupational skill and year fixed effects.

Figure 5: Graphic representation of the first stage

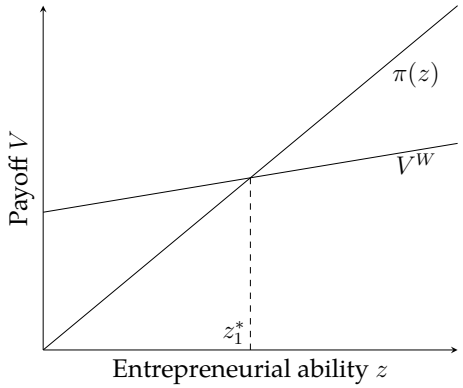


(a) Immigration Episode and Instrument

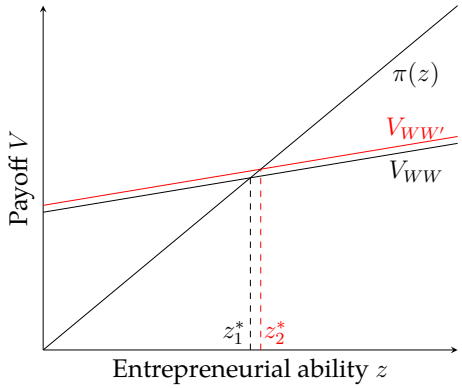
(b) Immigration Episode and Instrument, Netting Out Covariates

Note: The plots show scatterplots of the immigration episode on the instrument across local industries. Lines of best fit, with their coefficients and standard errors on top. The size of each circle corresponds to the baseline size of each local industry. Plot (a) provides the naive correlation. Plot (b) nets out industry and province fixed effects as well as controls from each variable. Therefore, these correspond to the coefficients in columns (1) and (4) from Table 4, respectively.

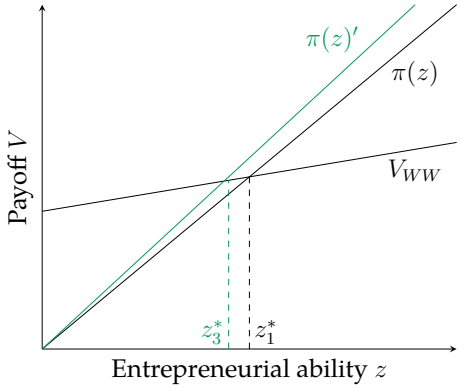
FIGURE 6: GRAPHIC INTUITION FOR COUNTERFACTUAL DECOMPOSITION OF THE IMPACT OF IMMIGRATION ON ENTREPRENEURIAL CHOICE



(a) Payoff V and entrepreneurial ability z



(b) Impact of immigration on native wages



(c) Impact of immigration on native profits

Note: The plots show how occupational choice reacts to an increase in immigration. Panel (a) shows how the payoff of entrepreneurship, $V_{EN}(z) = \pi(z)$, and the payoff of wage work, $V_{WW}(z) = z \times w_N$ evolve with entrepreneurial ability z, in the simplified case where there is only one education level. Panel (b) shows that an increase in immigration, and in presence of complementarity in production, the marginal product of native labour increases, thus increasing the returns to wage work. Panel (c) shows that an increase in immigration lowers immigrant wages and thus increases native profits, where the intersection between the $\pi(z)'$ and V'_{WW} shows the new equilibrium cutoff z_3^*. In Panel (c), all natives with $z \in [z_3^*, z_1^*]$ become entrepreneurs in this equilibrium, with respect to the baseline equilibrium shown in Panel (a). More information in Section 4.3.

Appendix A Data and Definitions

A.1 Definition of Entrepreneurship

My definition of entrepreneurship follows strictly the dictionary definition, by which an entrepreneur is "a person who makes money by starting or running businesses, especially when this involves taking financial risks" (OED, 2022). The self-employed individuals I identify in my data are an strict subset of people in this definition: they start and/or run businesses, and take a financial risk[44]. However, they do not necessarily overlap with innovators and successful business owners, which are what some other papers refer to as entrepreneurs.

In the MCVL, self-employed are those individuals who pay pension contributions under the self-employment scheme[45]. These are individuals who perform an economic activity for profit. For incorporated businesses, the requirement to pay pension contributions under the self-employment scheme is to have effective control of the business. In the Spanish system, an individual is attributed effective control if:

- At least half of the business capital is owned by people in the same household or family members up to second-degree relatives.
- At least a third of the business capital is under the individual ownership.
- At least a quarter of the business capital is under the individual ownership, and the individual has managerial duties.

Therefore, the self-employed category in the MCVL data captures most business owners, but one must note that in large firms, where ownership structure is usually more complex, the main owner or founder might not necessarily appear as self-employed in the data. This is less of a problem given the Spanish context, where most firms are small. For instance, by 2008, 95% of Spanish firms had less than 10 employees.

Finally, it is worth noting that the composition of self-employment during the 1999-2008 period is arguably different to that of succeeding periods, such as self-employed in the post Great Recession period[46]. This is because of two reasons. First, economic conditions during the 1999-2008 made the opportunity cost of becoming self-employed higher, as labour demand was much higher than in preceding and subsequent periods. Second, the recent rise in the gig economy and the false self-employed phenomena has increased the number of self-employed who are de facto employees. These may systematically differ

[44] Unincorporated self-employed respond to debt and liabilities accrued by their business with all their personal assets, while incorporated self-employed respond only with their business capital.

[45] Consult here for more information (in Spanish).

[46] A transformation of self-employment has been documented in the US economy by Colaiacovo et al. (2022).

from other types of self-employed individuals.

A.2 Additional information on the data

Muestra Contínua de Vidas Laborales. The MCVL is a 4% non-stratified random sample of individuals who interacted with Social Security each year, which includes information on their working histories. These are obtained from administrative records that match Social Security records with the Padrón Contínuo. The sample was first drawn in 2004, and each subsequent year some individuals leave the sample (due to not interacting with Social Security in that year). Therefore, new observations are added in order to maintain representativeness. In this project, I use the 2013 version because it is the first that includes information on whether self-employed are incorporated or not. Therefore, I use the MCVL retrospectively, as some other recent studies (Iraizoz-Olaetxea, 2022), which potentially loses some representativeness. This is less of a problem going back only to 1999 and focusing on the Spanish baby-boom cohort, as people born between 1954 and 1979 were likely to participate by then, but also in 2013, in the social security system. Among this group, 92% of the individuals present in the MCVL version of 2013 were present in the MCVL version of 2007. Moreover, the main results, except by whether the entrepreneur is incorporated or incorporated, which is not available pre-2013, remain very similar using the MCVL data starting from 2007.

Padrón Contínuo. This administrative data represent a yearly snapshot of people residing in each of the more than 8000 municipalities in Spain. This data are collected by each municipality and updated each year. The public access data contain information on province, age, nationality and place of birth. Individuals are strongly encouraged to register in a municipality, as it offers access to free public healthcare and schooling, it is the main proof of residence in the country, a main requirement to apply for legalisation, and undocumented immigrants can register as they face no threat of prosecution (Gonzalez and Ortega, 2013). Hence, the data are one of the best proxies possible administrative proxies of immigrant population, although it may miss temporary-workers or those who do not register. In any case, this data are used for the sampling of the labour force survey, which I describe below.

Encuesta de Población Activa. The Encuesta de Población Activa, or EPA, is the Spanish labour force survey, conducted quarterly on a representative sample of around 65,000 households (180,000 individuals). I use the EPA in 1999 and 2008 to calculate the shares of immigrants working in each local industry, and in 1999 exclusively to calculate baseline controls, namely the native share of high education (more than secondary education), the

share of males and the share of entrepreneurs in each local industry, as well as the overall immigrant distribution across industries in order to construct the instrument. I use the EPA to calculate these controls due to the possibly more representative coverage and inclusion of informal workers[47].

1991 Census. The Spanish National Institute of Statistics (Instituto Nacional de Estadística, INE) provides tabulated data from the 1991 Census data. For the construction of the instrument, I use data on population by country of origin across provinces in 1991. Access to microdata is not available, and tabulated data depends on the degree of aggregation. More disaggregated data than counts of individuals by country of origin (birth) at the province level is not available. Moreover, further disaggregated data by country of origin and industry in which the person works is not available.

[47] By 2000, Bosch and Farré (2014) estimate that around around 20 to 30% of workers working informally from 2000 to 2009, with a peak of 40% in 2005 before the 2005 regularisation. Due to the survey data of the EPA, this is possibly a lower bound.

Appendix B Additional Tables and Figures

Table B1: Robustness of the main specification

	(1) Δ Employment	(2) Δ Wage Workers	(3) Δ Entrepreneurs	(4) Δ Unincorporated	(5) Δ Incorporated	(6) Δ Wage
Panel A: Dropping Barcelona						
Δ Immigration Shock	-0.115	-0.311	0.196*	0.011	0.185***	0.944
	(0.55)	(0.52)	(0.10)	(0.08)	(0.06)	(0.74)
First-stage KP	13.23	13.23	13.23	13.23	13.23	13.23
Observations	245	245	245	245	245	245
Panel B: Dropping Madrid						
Δ Immigration Shock	-0.566^{+}	-0.754**	0.188***	0.019	0.169***	0.691
	(0.37)	(0.36)	(0.07)	(0.06)	(0.04)	(0.48)
First-stage KP	14.95	14.95	14.95	14.95	14.95	14.95
Observations	245	245	245	245	245	245
Panel C: Dropping Madrid and Barcelona						
Δ Immigration Shock	-0.322	-0.473	0.151^{+}	-0.022	0.172***	0.798
	(0.59)	(0.56)	(0.10)	(0.08)	(0.06)	(0.79)
First-stage KP	10.16	10.16	10.16	10.16	10.16	10.16
Observations	240	240	240	240	240	240
Panel D: Dropping agriculture industry						
Δ Immigration Shock	0.035	-0.177	0.212***	0.019	0.193***	0.915**
	(0.33)	(0.33)	(0.07)	(0.06)	(0.04)	(0.37)
First-stage KP	18.39	18.39	18.39	18.39	18.39	18.39
Observations	200	200	200	200	200	200
Panel E: Droping bottom 5 and top 5 percentile						
Δ Immigration Shock	-0.227	0.775	0.251***	0.058	0.159***	0.797***
	(0.84)	(0.85)	(0.06)	(0.04)	(0.03)	(0.31)
First-stage KP	3.15	4.44	19.71	20.94	13.63	22.13
Observations	225	225	226	225	225	225
Panel F: Using local-industry denominator for outcome						
Δ Immigration Shock	1.224	0.815	0.409^{+}	0.011	0.398***	0.583*
	(0.93)	(0.87)	(0.28)	(0.23)	(0.12)	(0.35)
First-stage KP	23.11	23.11	23.11	23.11	23.11	23.11
Observations	250	250	250	250	250	250
Panel G: Using local industry denominators, OLS						
Δ Immigration Shock	0.077**	0.037	0.040***	0.025**	0.015**	-0.010
	(0.04)	(0.03)	(0.01)	(0.01)	(0.01)	(0.06)
Observations	225	225	225	225	225	225
Panel H: No weights						
Δ Immigration Shock	-0.169	-0.344	0.175***	0.086**	0.089***	-1.545^{+}
	(0.31)	(0.29)	(0.05)	(0.04)	(0.02)	(0.98)
First-stage KP	40.90	40.90	40.90	40.90	40.90	40.90
Observations	250	250	250	250	250	250

Note: This table provides the estimates from estimating β from Equation 3 using IV and controls, but providing a robustness check in each Panel. Each robustness check is explained in Section 3.4. Each column corresponds to an outcome, namely, a difference in the number of immigrant individuals in a given occupational category from 1999 to 2008 in a local industry normalised by baseline province employment for Columns (1) to (5), and to the change in log wages during the same period in Column (6). Additional information on the outcome variables, the immigration episode, or the specification is in Sections 1 and 2. Robust standard errors are provided in parenthesis. Observations are weighted by baseline local industry employment. . Finally, I provide first-stage Kleibergen-Paap rk Wald F statistics and the total number of observations used in the estimation. Significance levels: $^{+}p < 0.15$,* $p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

Table B2: Robustness to micro-level specification

	Inflows			Outflows		
	(1) Entrepreneurship	(2) Uninc	(3) Inc	(4) Entrepreneurship	(5) Uninc	(6) Inc
Δ Immigration Shock	0.390***	0.185*	0.205***	-0.022	-0.015	-0.007
	(0.12)	(0.10)	(0.05)	(0.02)	(0.01)	(0.01)
Observations	462202	462202	462202	462202	462202	462202

Note: This table provides the estimates from estimating β from the equation $E_{j,ip} = \beta \frac{N^{F}_{ip,2008} - N^{F}_{ip,1999}}{WAP_{p,1999}} + \gamma X_{ip,1999} + \gamma_p + \gamma_i + \epsilon_{ip}$. The right-hand side is the same as in Equation 3, but the dependent variable is an indicator variable equal to 1 if the person j in the local industry ij in 2008 was an entrepreneur, unincorporated entrepreneur (*Uninc*) or incorporated entrepreneur (*Inc*) in 2008 but not in 1999, and 0 otherwise, in the first three columns. In the last three columns, the variable takes value equal to 1 if the person j in local industry ip in 1999 was an entrepreneur, unincorporated entrepreneur (*Uninc*) or incorporated entrepreneur (*Inc*) in 1999 but not in 2008, and 0 otherwise. Robust standard errors are provided in parenthesis. The first-stage Kleibergen-Paap rk Wald F statistics is the same as in Table 5. Each observation is a native individual from the analysis sample. Significance levels: $^{+}p < 0.15,^{*} p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table B3: Robustness of the SSIV to multiple instrumentation

	(1) Δ Employment	(2) Δ Wage Workers	(3) Δ Entrepreneurs	(4) Δ Unincorporated	(5) Δ Incorporated	(6) Δ Wage
Δ Immigration Shock, 1999-2008	0.122	-0.253	0.375***	0.162**	0.213***	0.040
	(0.42)	(0.39)	(0.10)	(0.07)	(0.04)	(0.44)
Δ Immigration Shock, 1996-1999	0.111	1.656	-1.545^{+}	-1.204*	-0.341	5.873
	(4.38)	(4.16)	(1.00)	(0.67)	(0.52)	(4.94)
First-stage KP	7.75	7.75	7.75	7.75	7.75	7.75
Observations	250	250	250	250	250	250

Note: This table provides the estimates from estimating β from Equation 3 using the multiple instrumentation procedure suggested by Jaeger et al. (2019), i.e. controlling for lag immigration increases and instrumenting for both predicted current and lagged immigration increases. Each column corresponds to an outcome, namely, a difference in the number of immigrant individuals in a given occupational category from 1999 to 2008 in a local industry normalised by baseline province employment for Columns (1) to (5), and to the change in log wages during the same period in Column (6). Additional information on the outcome variables, the immigration episode, or the specification is in Sections 1 and 2. Robust standard errors are provided in parenthesis. Observations are weighted by baseline local industry employment. Finally, I provide first-stage Kleibergen-Paap rk Wald F statistics and the total number of observations used in the estimation. Significance levels: $^{+}p < 0.15,^{*} p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table B4: Robustness of the SSIV to leave-one-out and push-factors specifications

	(1) Δ Employment	(2) Δ Wage Workers	(3) Δ Entrepreneurs	(4) Δ Unincorporated	(5) Δ Incorporated	(6) Δ Wage
Panel A: Baseline instrument						
Δ Immigration Shock	0.132	-0.100	0.232***	0.051	0.181***	0.583*
	(0.30)	(0.29)	(0.06)	(0.05)	(0.03)	(0.35)
First-stage KP	23.11	23.11	23.11	23.11	23.11	23.11
Panel B: Push-factors instrument						
Δ Immigration Shock	0.272	-0.011	0.283***	0.084^{+}	0.199***	0.616^{+}
	(0.33)	(0.32)	(0.07)	(0.05)	(0.04)	(0.42)
First-stage KP	17.10	17.10	17.10	17.10	17.10	17.10
Panel C: Leave one out instrument						
Δ Immigration Shock	0.036	-0.189	0.225***	0.045	0.180***	0.581
	(0.33)	(0.32)	(0.07)	(0.05)	(0.03)	(0.40)
First-stage KP	15.41	15.41	15.41	15.41	15.41	15.41
Observations	250.000	250.000	250.000	250.000	250.000	250.000

Note: This table provides the estimates from estimating β from Equation 3 using different IV procedures. Panel A provides the baseline results, while Panels B and C use either a push-factors instrument or a leave-one-out, respectively. Each column corresponds to an outcome, namely, a difference in the number of immigrant individuals in a given occupational category from 1999 to 2008 in a local industry normalised by baseline province employment for Columns (1) to (5), and to the change in log wages during the same period in Column (6). Additional information on the outcome variables, the immigration episode, or the specification is in Sections 1 and 2. Robust standard errors are provided in parenthesis. Observations are weighted by baseline local industry employment. Finally, I provide first-stage Kleibergen-Paap rk Wald F statistics and the total number of observations used in the estimation. Significance levels: $^{+}p < 0.15$,* $p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

Table B5: Exogeneity of Initial Shares of Country-of-Origin Groups, OLS (Goldsmith-Pinkham et al. 2020)

Country-of-Origin Group:	Employment	Wage Work	Entrepreneurship	Uninc. Entrepreneurship	Inc. Entrepreneurship
Germany	0.451	0.691	-0.240^{+}	-0.209	-0.031
	(0.68)	(0.64)	(0.16)	(0.16)	(0.03)
Argentina	-0.772	-0.607	-0.164	-0.162	-0.002
	(0.59)	(0.55)	(0.19)	(0.18)	(0.04)
Bolivia	1.310*	1.355*	-0.046	-0.060	0.014
	(0.70)	(0.70)	(0.17)	(0.16)	(0.04)
China	0.087	0.142	-0.055^{+}	-0.045	-0.010^{+}
	(0.13)	(0.13)	(0.04)	(0.03)	(0.01)
Colombia	0.519	0.318	0.201	0.216	-0.015
	(1.54)	(1.53)	(0.29)	(0.28)	(0.05)
Ecuador	0.329	0.380	-0.052	-0.021	-0.031
	(0.67)	(0.66)	(0.16)	(0.15)	(0.03)
Italia	-0.290	-0.991	0.701***	0.600***	0.101***
	(0.85)	(0.87)	(0.17)	(0.16)	(0.04)
Morocco	0.238	0.759	-0.521^{+}	-0.439^{+}	-0.082^{+}
	(1.27)	(1.30)	(0.32)	(0.30)	(0.06)
Peru	-0.913	-0.744	-0.169	-0.192	0.023
	(0.99)	(0.94)	(0.22)	(0.21)	(0.06)
Portugal	-0.671^{+}	-0.646*	-0.025	-0.010	-0.015
	(0.42)	(0.39)	(0.12)	(0.11)	(0.03)
Rest Africa	-0.642	-0.877	0.235	0.155	0.080
	(1.23)	(1.29)	(0.30)	(0.29)	(0.06)
Rest Americas	0.379	0.214	0.165	0.173	-0.007
	(0.58)	(0.55)	(0.13)	(0.12)	(0.03)
Rest Asia/Oceania	0.097	0.218	-0.121	-0.111	-0.010
	(0.42)	(0.41)	(0.11)	(0.10)	(0.02)
Rest Europe	-0.214	0.164	-0.378^{+}	-0.321	-0.057
	(0.44)	(0.41)	(0.24)	(0.23)	(0.04)
Romania	-1.054**	-1.126**	0.072	0.085	-0.013
	(0.52)	(0.49)	(0.09)	(0.09)	(0.03)
United Kingdom	-0.483	-0.710*	0.227*	0.195^{+}	0.032
	(0.42)	(0.41)	(0.13)	(0.13)	(0.03)

Note: This table shows independent regressions of pre-period outcomes on country-of-origin shares, and its associated coefficients. The dependent variables are the initial shares of country-of-origin groups across provinces (1991) and industries (1999), regressed on changes in pre-period outcomes from 1990 to 1999. Each specification includes baseline controls and fixed effects. Observations are weighted by baseline local industry employment. Robust standard errors are provided in parenthesis. Significance levels: $^{+}p < 0.15$,$^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$.

Table B6: Employment and wage effects of immigration on immigrants

	(1) Δ Employment	(2) Δ Wage Workers	(3) Δ Entrepreneurs	(4) Δ Unincorporated	(5) Δ Incorporated	(6) Δ Wage
Δ Immigration Shock	0.443***	0.415***	0.028^{+}	0.027*	0.000	-2.021
	(0.06)	(0.05)	(0.02)	(0.02)	(0.00)	(2.69)
Mean dep. var	2.15	1.88	0.27	0.22	0.04	-1.82
First-stage KP	23.11	23.11	23.11	23.11	23.11	23.11
Observations	250	250	250	250	250	250

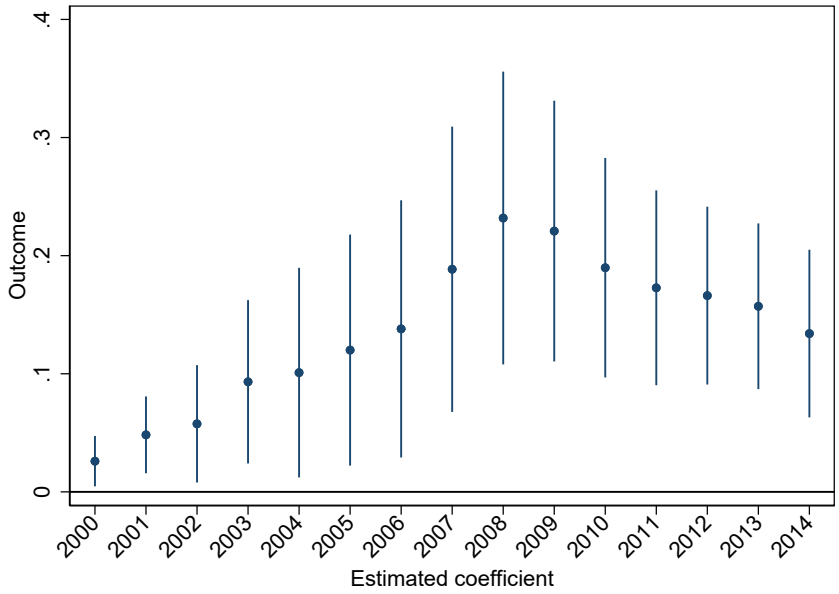
Note: This table provides the estimates from estimating β from Equation 3 using IV and controls. Each column corresponds to an outcome, namely, a difference in the number of immigrant individuals in a given occupational category from 1999 to 2008 in a local industry normalised by baseline province employment for Columns (1) to (5), and to the change in log wages during the same period in Column (6). Additional information on the outcome variables, the immigration episode, or the specification is in Sections 1 and 2. Robust standard errors are provided in parenthesis. Observations are weighted by baseline local industry employment. The Table provides the mean of each dependent variable in percentage terms (multiplied by 100), as well as baseline shares of each employment category in Columns (2) to (6). Finally, I provide first-stage Kleibergen-Paap rk Wald F statistics and the total number of observations used in the estimation. Significance levels: $^{+}p < 0.15,^{*} p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table B7: Native Worker Flows across Local Industries

	(1) Net	(2) Same Local Industry	(3) Same Province Different Industry	(4) Different Province Same Industry	(5) Different Province Different Industry
Panel A: Inflows					
Δ Immigration Shock	-0.002	-0.390	0.581***	-0.186***	-0.007
	(0.35)	(0.29)	(0.13)	(0.07)	(0.02)
Panel B: Outflows					
Δ Immigration Shock	0.098	0.167**	-0.113^{+}	0.038	0.006
	(0.16)	(0.07)	(0.08)	(0.04)	(0.02)
First-stage KP	23.11	23.11	23.11	23.11	23.11
Observations	250	250	250	250	250

Note: This table provides the estimates from estimating β from Equation 3 using the migrant networks instrument detailed in Section 2 and controls. Panel A estimates inflows into wage work in a local industry, while Panel B estimates outflows. Inflows are defined as the number of people that were wage workers in 2008 in a given local industry but not in 1999 (Column 2), or alternatively they were in 1999 in the same province but another industry (Column 3), in a different province but in the same industry (Column 4), and in a different province and industry (Column 5). Outflows are defined analogously. Additional information the immigration episode or the specification is in Sections 1 and 2. Robust standard errors are provided in parenthesis. Observations are weighted by baseline local industry employment. The Table provides the mean of each dependent variable in percentage terms (multiplied by 100). Finally, I provide first-stage Kleibergen-Paap rk Wald F statistics and the total number of observations used in the estimation. Significance levels: $^{+}p < 0.15,^{*} p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

FIGURE B1: DYNAMIC EFFECTS OF THE IMMIGRATION EPISODE ON ENTREPRENEURSHIP



Note: This figure provides the estimates from estimating β from Equation 3 using IV and controls, but varying the dependent variable to differences between each year with respect to 1999. All estimates include 95% confidence intervals constructed with robust standard errors. Observations are weighted by baseline local industry employment.

Appendix C Evolution of Immigrant Wages

Reliable yearly data on immigrant wages between 1999 and 2008 is unavailable due to limitations in existing data sources. Administrative labour income data (MCVL) covers only the formal sector, where immigrants are under-represented. The Wage Structure Survey (Encuesta de Estructura Salarial, EES) includes formal firms but is conducted every four years starting in 2002.[48] The National Immigrant Survey (Encuesta Nacional de Inmigrantes, ENI) provides income data for both documented and undocumented immigrants but was conducted only in 2007. Lastly, the Spanish Labour Force Survey (EPA) does not collect wage information.[49]

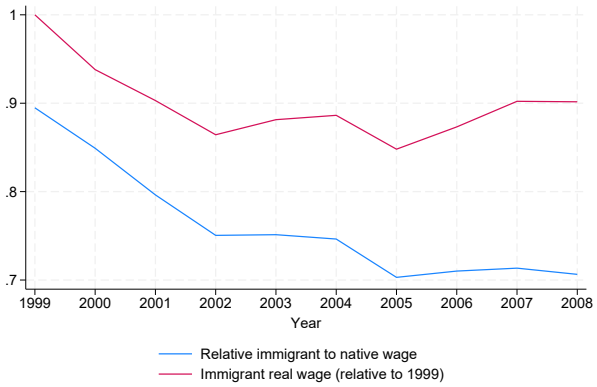
Despite these challenges, I provide evidence that immigrant wages declined between 1999 and 2008. Using MCVL data, I show that in the formal sector, both real wages and wages relative to natives decreased during this period. Survey data from the EES supports these findings, while ENI data reveals that undocumented immigrants earn less than documented ones. The latter confirms formal wages overestimate actual immigrant wages, as undocumented immigrants, restricted to informal work, typically earn less. Given that the share of immigrants working informally increased steadily during this period, the decline in overall immigrant wages is likely even greater.

Administrative data. Figure C1 uses data from the MCVL from 1999 to 2008 to calculate real immigrant daily wages as well as relative daily wages of immigrants to those of natives. In both cases, there is a decrease. Real wages of immigrants decrease by 10% during the period. However, in order to compare immigrant wages in the context of the labour market, I also provide relative wages of immigrants with respect to natives. At the beginning of the period, in 1999, immigrant wages are 90% of those of natives. By 2008, this ratio drops to 70%. This is driven both by the decrease in real immigrant wages and by an increase of native real wages by around 13%.

[48] It was first conducted seven years before, in 1995. This wave does not include country of origin.

[49] It is possible to obtain imputed data from administrative records, but actual wage information from surveyed individuals does not exist. The imputed data would not be useful for this project as it is only available from 2006.

Figure C1: Real and relative immigrant daily wages, MCVL



Note: The figure provides the decrease in daily immigrant wages, both in real and relative terms, for the period 1999 to 2008 using information data from the MCVL. Daily immigrant wages are total yearly earnings divided by total days worked in a year among immigrants aged 20 to 60 years old. Real wages are deflated using national cumulative inflation during the period of interest.

Wage Structure Survey data. In Table C1, I report the yearly earnings and hourly wages calculated using the Wage Structure Survey (EES) data. In Panel A, I provide the quantities in real terms, while in Panel B I report relative quantities, using information on natives. In both cases, we can observe a decrease from 2002 to 2006 in both yearly earnings and hourly wages. In real terms, there is a small increase in both this quantities from 2006 to 2010, while compared to natives, these stay constant during this time period. The results are largely consistent with the administrative data reported in Figure C1. However, the relative decrease from 2002 to 2006 is larger than that documented from the administrative data.

Table C1: Yearly earnings and hourly immigrant wages, EES

	2002	2006	2010
Panel A: Real terms			
Yearly earnings (1000 euros)	13.3	10.5	11.5
Hourly wages	8	6.4	7.5
Panel B: Relative to natives			
Yearly earnings (1000 euros)	0.71	0.64	0.65
Hourly wages	0.71	0.64	0.66

Note: The table provides yearly earnings and hourly wages, both in real and relative (to natives) terms, for the years 2002, 2006 and 2010, using data from EES. The estimates are not conditional on age as it is not available in the EES.

National Immigrant Survey data. Table C2 displays the monthly earnings and hourly wages of immigrants surveyed in the 2007 National Immigrant Survey, conditioning on period of arrival. Monthly earnings and hourly wages of immigrants arrived before 2000 are around 15% higher than those of immigrants arrived after 1999, partially reflecting differences in sociodemographic characteristics like age, experience, country of origin composition, as well as differences in shares of undocumented immigrants. Immigrants arrived after 1999 have larger rates of undocumented status, thus indicating that at least 15% of them can only work informally. Monthly earnings and hourly wages of undocumented immigrants are substantially lower, indicating that the quality of jobs they are employed in, as well as the wages they are willing to accept, are lower. This information is complementary to the numbers shown in Figure C1 and Table C1. More concretely, formal labour market earnings represent an upper bound of actual labour market earnings of immigrants, due to the participation of immigrants in the informal labour market where wages are lower. Taking all the information shown in this section together, and since informal rates increased steadily during the period of analysis[50], it is plausible to conclude that the decrease in immigrant wages is likely larger than that suggested by Figure C and Table C1. The actual decrease is hard to pin down due to the fact that the size of the informal sector cannot be exactly measured.

Table C2: Monthly earnings and hourly wages of immigrants, by documentation status, ENI

	All	Documented	Undocumented
Panel A: Arrived before 2000			
Monthly earnings	1218	1239	702
Hourly wages	7.7	7.8	5.3
Share	1	0.97	0.03
Panel B: Arrived after 1999			
Monthly earnings	1059	1111	784
Hourly wages	6.5	6.8	5.4
Share	1	0.85	0.15

Note: The table provides monthly earnings and hourly wages of immigrants, by documentation status, for the year 2007. The survey was conducted between November 2006 and February 2007, with reference date on 1st January 2007. Shares are conditional on arrival year; the share of immigrants arrived before 2000 over total immigrants in 2007 is 12.75%.

[50] Not monotonically due to the 2005 regularisation.

Appendix D Model Appendix

D.1 Details on the calibration

I calibrate the model by matching empirical moments with models generated by the model. The calibration procedure can be described as follows:

1. **Choose functional forms for the primitives of the model.** I let the production function of entrepreneurs to be a CES production function, as many of the literature. I consider only native workers and immigrants for simplicity, although in Appendix D.2 I provide an extension of this model by considering two education models. For the ability distribution of natives, I follow Poschke (2018) and assume a log-normal distribution with mean μ_z and variance σ_z^2. I choose a log-normal rather than Pareto distribution due to its higher flexibility.
2. **External calibration**. To reduce the amount of parameters that I need to internally calibrate, I take the decreasing returns to scale parameter $\alpha = 0.9$, so the profit share of income is 10%, following Poschke (2018).
3. **Internal calibration**. There are four parameters to calibrate internally: the elasticity parameter ρ that determines the substitution or complementarity between immigrant and native workers ρ, the relative productivity of immigrants parameter a, and the mean and variance of the log-normal distribution of natives' ability, μ_z and σ_z^2. To bring the model to the data, I select four moments that are directly related with the model: baseline relative wages of natives and immigrants, $\frac{w_N^b}{w_I^b}$, the relative change in native wages, $\frac{w_N^a}{w_N^b}$, the baseline share of native entrepreneurs, $\frac{Entr_N^b}{Employment_N^b}$, and the percentage point increase in native entrepreneurs, $\frac{Entr_N^a - Entr_N^b}{Employment_N^b}$. The a and b superscripts refer to the "after" (2008) and "before" (or baseline, 1999) scenarios, characterised with immigrant shares of 14 and 2.14 per cent, respectively. To perform the calibration, I consider the vector of data moments as a function of parameters $\theta = \{\rho, a, \mu_z, \sigma_z^2\}$, which I call $\hat{m}(\theta)$. Model moments are $m(\theta)$. The calibrated parameters are the solution $\hat{\theta}$ to the following minimisation problem:

$$\hat{\theta} = \arg\min_{\theta} (\hat{m}(\theta) - m(\theta))' W (\hat{m}(\theta) - m(\theta))$$

where W is a diagonal 4×4 matrix where the diagonal elements are the data moments corresponding inverse of the variance, so the more precisely estimated empirical moments obtain a higher weight. In the minimisation procedure, I start by guessing parameters θ. Then, I simulate the model with before and after immigra-

tion shares, obtain the model moments, calculate its difference, and update until the distance is minimised. I do this procedure in a grid of parameters in the space characterised by $\rho = [0, 1]$, $a = [0, 1.5]$, $\mu_z = [0, 2]$ and $\sigma_z^2 = [0, 2]$. The solution that minimises the sum of weighted distances is given in Table 11.

4. **Model validation**: in order to validate the model, I look at the main non-targeted moment, which is the change in immigrant wages, $\frac{w_I^a}{w_I^b}$, which the model predicts to be 0.35. Data estimates are around 0.7-0.9, which are substantially higher. However, since the model is very simple, matching the actual magnitude of the decrease in immigrant wages becomes a lesser concern. Matching the fact that immigrant wages decrease remains more important.

D.2 Model extension: two education levels

In this section a present extension of the model with two education levels.

Set-up. Native individuals can choose whether to be wage workers or entrepreneurs, depending on the value V of each choice. Natives draw their ability z from a education-specific distribution with pdf f_j, where education can be high (H) or low (L), $j \in \{H, L\}$. The ability can be thought of as skill differences or differing labour supply endowments within educational levels. If they become wage workers, they obtain labour earnings composed of their education-specific wage times their ability z:

$$V_{WW}^j = z^j \times w_N^j, \quad j \in \{H, L\}$$

If they become entrepreneurs, they employ $h(z)$ high-educated (HE) natives, $\ell(z)$ low-educated (LE) natives, and $i(z)$ immigrants to produce an output $Q(z)$ that depends on their ability z:

$$Q(z) = z\left[a(bi(z)^\gamma + \ell(z)^\gamma)^{\frac{\rho}{\gamma}} + h(z)^\rho\right]^{\frac{\alpha}{\rho}} = zL(z)$$

where a is the relative efficiency of LE workers with respect to HE native workers, b is the relative efficiency of immigrants with respect to LE native workers. Then, $\alpha < 1$ is a decreasing returns to scale parameter, as in Lucas (1978). Finally, and most importantly, γ and ρ govern the degree of substitution/complementarity between LE natives and immigrants, and HE native workers and LE workers, respectively, with $\gamma \leq 1$ and $\rho < 1$.

Under constant returns to scale, HE natives are always complements in employment with respect to immigrants. For LE, it depends on the value of γ: the closer the value to 1, the most likely it is that the marginal product of LE labour decreases when immigration increases, all else fixed. In the presence of decreasing returns to scale, the values of γ

and ρ that make natives and immigrants substitutes or complements in employment are different. To allow complementarity among HE natives and immigrants, it is sufficient to have $\rho < \alpha < 1$. For LE natives and immigrants, the degree of substitutability depends on γ, but from the first order condition in Equation 12 it can be seen that whether $\partial w_N^L / \partial i \lesseqgtr 0$ depends on α as well. I don't make any prior assumption on whether natives and immigrants are substitutes or complements, and thus on the values of γ and ρ.

By using two levels of education, the model can endogenously capture the positive correlation between ability and wages suggested by the previous literature. Different skill levels allow for different degrees of complementarity or substitutability between immigrants and natives with different education levels in the labour market, given by $\rho \neq \gamma$.

The value of being an entrepreneur will be equal to the profit $\pi(z)$. Profit is defined as output minus labour costs. The latter are determined by native and immigrant wages, respectively w_N^j and w_I, taken as given by the entrepreneur:

$$V_{EN}(z) = \pi(z) = zL(z) - w_I i(z) - w_N^H h(z) - w_N^L \ell(z)$$

Equilibrium. The equilibrium is defined analogously as in the case for one education level: an equilibrium of this economy consists of wage rates w_N^H, w_N^L, and w_I such that taking wages as given, natives choose optimally between employment and entrepreneurship, entrepreneurs demand inputs optimally, and the labour market clears. The first order conditions for optimal input choice are:

$$w_I = z\alpha \left[a(bi(z)^\gamma + l(z)^\gamma)^{\frac{\rho}{\gamma}} + h(z)^\rho \right]^{\frac{\alpha-\rho}{\rho}} ab(bi(z)^\gamma + l(z)^\gamma)^{\frac{\rho-\gamma}{\gamma}} i(z)^{\gamma-1} \tag{11}$$

$$w_N^L = z\alpha \left[a(bi(z)^\gamma + l(z)^\gamma)^{\frac{\rho}{\gamma}} + h(z)^\rho \right]^{\frac{\alpha-\rho}{\rho}} a(bi(z)^\gamma + l(z)^\gamma)^{\frac{\rho-\gamma}{\gamma}} l(z)^{\gamma-1} \tag{12}$$

$$w_N^H = z\alpha \left[a(bi(z)^\gamma + l(z)^\gamma)^{\frac{\rho}{\gamma}} + h(z)^\rho \right]^{\frac{\alpha-\rho}{\rho}} h(z)^{\rho-1} \tag{13}$$

Wages are determined in equilibrium by labour market clearing and the optimal occupational choice condition. The first condition implies that the labour supply of each factor is equal to its demand by firms. Labour supply by natives is given by LS_N^j, for each education level j. Labour supply for immigrants is given by LS^I. Labour supply for natives is determined endogenously, while labour supply for immigrants is exogenous as they do not own firms and supply their labour inelastically. Labour market clearing conditions

can be written as follows:

$$LS_N^H = \int_{z^{*H}} f_H(z)n(z)dz + \int_{z^{*L}} f_L(z)n(z)dz \tag{14}$$

$$LS_N^L = \int_{z^{*H}} f_H(z)\ell(z)dz + \int_{z^{*L}} f_L(z)\ell(z)dz \tag{15}$$

$$LS_I = \int_{z^{*H}} f_H(z)i(z)dz + \int_{z^{*L}} f_L(z)i(z)dz \tag{16}$$

Native labour supply is determined by cut-offs z^{*j}. These cut-offs are obtained from the optimal occupational choice conditions, which define marginal entrepreneurs with ability z^{*j} that are indifferent between wage work and entrepreneurship:

$$\pi(z^{H*}) = w_N^H(z^{H*}) \tag{17}$$

$$\pi(z^{L*}) = w_N^L(z^{L*}) \tag{18}$$

Calibration. The calibration is analogous to the case with one education level. On top of $\alpha = 0.9$ and that z follows a log-normal distribution with mean μ_j and variance σ_j^2 depending on education level j, I choose the share of low-educated entrepreneurs to match the data.

However, in this case I have to estimate eight, rather than four moments, namely $\theta = \{\rho, \gamma, a, b, \mu_L, \mu_H, \sigma_L^2, \sigma_H^2\}$. Hence, I match based on eight moments: baseline shares of entrepreneurship by education, and relative wages of high-educated with respect to low-educated natives, and of low-educated natives with respect to immigrants. Dynamic moments include increases in entrepreneurship and wages for natives of each education level, calculated using the treatment effects identified in Table 6.

Table 11 presents the results of the calibration. The model closely matches the data moments at baseline and performs well in capturing the dynamics of entrepreneurship and wages following the immigration episode. However, it does not capture a wage decrease among high-educated workers. This is likely due to the model assuming a fixed number of natives in the economy: as more high-educated natives become entrepreneurs, the relative supply of high-educated wage workers declines, exerting upward pressure on their wages.[51] Despite this, the model successfully captures the key phenomenon of interest: the reallocation of native workers into entrepreneurship following an immigration shock,

[51] If additional high-educated natives entered the labour market—whether from other local industries disproportionately more than low-educated natives (Amuedo-Dorantes and De La Rica, 2011) or from non-employment (Michaillat, 2024)—the model could endogenously generate a smaller wage effect for high-educated natives. However, incorporating such a mechanism is beyond the scope of this paper.

making the calibration satisfactory.

The calibrated parameters are reasonable when interpreted through the lens of previous research. The substitution parameters ρ and γ from the right panel of Table D1 imply complementarity in employment, as an increase in immigration lead to an increase in the marginal product of both LE and HE natives.[52] Then, $1 > a = 0.67 > b = 0.31$ shows that workers in the low-educated and immigrants nest are less productive than high-educated natives, and also that immigrants are less productive than low-educated natives. The parameters μ_j and σ_j show that the distribution of entrepreneurial ability among high-educated has a higher mean but lower variance. Therefore, the model endogenously generates a positive correlation between wages and ability across education levels.

Table D1: Moments and parameters from extended model calibration

Moment	Data	Model
Entr. Rate HE, Before	0.113	0.114
Entr. Rate LE, Before	0.142	0.149
Entr. Rate HE, After	0.127	0.126
Entr. Rate LE, After	0.146	0.155
Baseline $\frac{w_N^H}{w_N^L}$	1.19	1.18
Baseline $\frac{w_N^L}{w^I}$	1.03	1.03
Δw_N^H	0.981	1.005
Δw_N^L	1.061	1.001

Parameter	Value
ρ	0.638
γ	0.656
a	0.679
b	0.312
μ_H	0.421
μ_L	0.205
σ_H^2	0.201
σ_L^2	0.418

Note: The left table provides moments used in the estimation of the extended model of occupational choice and immigration laid out in Appendix D.2 The right table provides the parameters and calibrated values. ρ and γ are the substitution parameters for high-educated and low-educated/immigrant nest, and immigrants and low-educated natives, respectively. Parameters a and b are relative productivity of low-educated nest of the CES production function and relative productivity of immigrants within the low-educated nest in the CES production function, respectively. The parameters μ_j and σ_z^j for $j \in \{L, H\}$ are the mean and standard deviation of the log-normal distribution of entrepreneurial ability for each education level.

Finally, the model predicts that immigrant wages in 2008 are 50.4% of its real value in 1999, higher than in the model with only one education level. Still, the 50% decrease predicted by the extended model is most likely an overestimate of the actual magnitude of the immigrant wages decrease.

Counterfactual decomposition with the extended model. Now, I turn to the counterfac-

[52] This can be shown numerically by taking the production function of any entrepreneur and increasing immigration while keeping native employment fixed. In fact, with the current estimates of ρ and γ, HE natives' wages increase more than those of LE natives when immigration increases, i.e. $\partial w_N^H/\partial i > \partial w_N^L/\partial i > 0$. However, the magnitude of the effect is small in the model.

tual decomposition explained in Section 4.3 but for the extended model with two education levels. The decomposition is provided in Table D2, where the first column refers to the post-immigration episode. The results are analogous to the counterfactual decomposition with the original model.

Counterfactual: occupational choice depends only on native wages. The second column of Table D2 provides the results of this counterfactual. Keeping potential profits fixed at baseline, without the immigration increase, makes natives' labour supply choices depend only on wage changes induced by the immigrant labour supply shock. Wages of HE natives increase more than those of LE natives due to the immigration increase. This is because the former are more complementary with respect to immigrants, as the marginal product of HE natives in production increases relatively more, all else fixed. Wage increases are also higher than in the After scenario due to positive entrepreneur selection: only the most productive entrepreneurs remain entrepreneurs. Regarding entrepreneur shares, both groups of natives see their entrepreneurship decrease when compared to the *Before* setting, but more so for HE natives, as the opportunity cost of entrepreneurship increases more due to higher wages. However, since the wage effects are small, entrepreneurship rates only decrease by 0.001pp for HE natives and by 0.0001pp for LE natives.

Counterfactual: occupational choice depends only on potential profits. The third column of Table D2 provides the results of this counterfactual. When native wages are fixed at baseline upon conditional choice, native occupational choices are driven by changes in potential profits. Since immigrants are perfect substitutes among themselves, an increase in immigration depresses immigrant wages. In turn, the potential profits curve shifts up for natives. The profit distribution for HE natives has a higher average and lower variance than LE natives, so HE natives entrepreneurship increases relatively more: the entrepreneurship rate for HE natives increases by 1.5pp, and by 0.4pp for LE natives. Finally, no constraints are introduced for the labour market clearing conditions in Equation 9-16, so the smaller amount of native wage workers also increases their wages

Taken together, the insights of the counterfactual decomposition are consistent with the ones from the simpler model with only one educational level.

Table D2: Counterfactual decomposition of the impact of immigration on native entrepreneurship, extended model

		Post immigration episode, occupational choice depends only on...	
	Post immigration episode	Native Wages	Potential Profits
High Educated Natives			
Δ Entrepreneur (pp)	0.014	-0.001	0.015
Low Educated Natives			
Δ Entrepreneur (pp)	0.004	-0.0001	0.004
Δ Wages (%)			
Immigrants	0.504	0.512	0.503
HE Natives	1.004	1.011	1.005
LE Natives	1.001	1.009	1.000

Note: The table displays key statistics for HE and LE native entrepreneurs, and wages, under the counterfactual composition described in Section 4.3. Each column shows a different scenario, with respect to the quantities in the baseline period before the immigration episode. The first column shows the actual After scenario. The second and third column show the equilibrium in the case when immigration impacts occupational choice either through native wages or native potential profits, respectively. The last column shuts down the entrepreneurial option, not allowing new entrepreneurs.